Expert System-Based Mineral Mapping in Northern Death Valley, California/Nevada, Using the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS)

F. A. Kruse*†, A. B. Lefkoff*, and J. B. Dietz*

*Center for the Study of Earth from Space (CSES), Cooperative Institute for Research in Environmental Sciences (CIRES), University of Colorado, Boulder, †Department of Geological Sciences, University of Colorado, Boulder

Integrated analysis of imaging spectrometer data and field spectral measurements were used in conjunction with conventional geologic field mapping to characterize bedrock and surficial geology at the northern end of Death Valley, California and Nevada. A knowledge-based expert system was used to automatically produce image maps showing the principal surface mineralogy from Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data. Linear spectral unmixing of the AVIRIS data allowed further determination of relative mineral abundances and identification of mineral assemblages and mixtures. The imaging spectrometer data show the spatial distribution of spectrally distinct minerals occurring both as primary rock-forming minerals and as alteration and weathering products. Field spectral measurements were used to verify the mineral maps and field mapping was extended to remote sensing data. Geographically referenced image maps produced from these data form new base maps from which to develop improved understanding of the processes of deposition and erosion affecting the present land surface.

INTRODUCTION

The objectives of this research were 1) to integrate remote sensing data and other "classic" geologic information for the Death Valley region to develop a better understanding of the geologic processes shaping the land surface and 2) to produce detailed 1:24,000-scale geologic maps that can be used in a regional synthesis. These studies place particular emphasis on the northern "termination" of the valley, a critical location in understanding regional tectonics.

Conventional geologic mapping, field and laboratory reflectance spectroscopy and remote sensing data sets were used to study portions of the extreme northern end of Death Valley California and Nevada, USA (Fig. 1). The "northern Grapevine Mountains" (NGM) study area shown in Figure 1 has been reported on in numerous proceedings papers (Kruse, 1987a; Kruse and Kierein-Young, 1990; Kruse, 1990a; Kruse and Dietz, 1991). This area is an unnamed northwestward extension of the range and does not actually
form part of the Grapevine Mountains proper. Most of the research here has concentrated on mapping of Jurassic-age plutons and associated hydrothermal alteration (Wrucek et al., 1984; Kruse, 1988; Kruse and Dietz, 1991); however, the nature and scope of these studies is much broader, pertaining to the geologic history and development of the entire Death Valley region. Details of the imaging spectrometer studies of the northern Grapevine Mountains area and initial results of the extension of this research to adjacent areas in northern Death Valley are reported here.

GEOLOGY

The geology of Death Valley is thought by many to be over studied and well understood. In fact, however, only one detailed regional synthesis exists (Hunt and Mabey, 1966), and much remains to be learned regarding the tectonics and geologic history of this region. While there are several excellent localized studies and geologic maps (Denny, 1965; Hunt and Mabey, 1966; Stewart et al., 1966; Stewart, 1967; Albers and Stewart, 1972), most of these are out of print or are of limited scope. The northern end of Death Valley has virtually been ignored; only reconnaissance mapping exists on the regional scale (Wrucek et al., 1984; Moring, 1986). Even high-quality topographic maps are just now becoming available for some portions of the region.

Death Valley is located at the southern edge of the Great Basin in the Basin and Range Province of California and Nevada (Fig. 1). It is bounded on both east and west by north-trending, block-faulted ranges (Hunt and Mabey, 1966). The valley forms a closed hydrologic system, famous for its extensive salt pans and spectacular landscapes. Geologically, the Death Valley region is extremely diverse. Mountain ranges surrounding the valley top out at elevations greater than 3350 m (11,000 ft) and are made up of rocks from Precambrian to Tertiary in age, ranging in composition from sediments, to granitic composition intrusions, to volcanic rocks spanning the range from basalt to rhyolite. Quaternary deposits include the salt pan deposits (evaporites), gravel fans and alluvium, lake deposits, and pediments. Complex faulting over long periods of time, including both late Mesozoic and Tertiary low angle detachment faulting and “recent” right lateral strike slip faulting make this region a challenging area for geologic mapping.

The main portion of the area mapped during this study (the NGM study area, Fig. 1) consists of about one third of the “West of Gold Mountain” U.S. Geological Survey 7 1/2 min quadrangle (1:24,000 scale). Some relatively detailed (1:62,500 scale) mapping has also been done in this area as part of U.S. Geological Survey Wilderness Assessment (WSA) Programs (Wrucek et al., 1984). Additional mapping of surficial deposits has been done at 1:62,500 scale (Moring, 1986). Precambrian bedrock in the NGM area consists of limestones, dolomites, sandstones, and their contact metamorphic equivalents; however, published geologic maps do not distinguish between the different lithologies. Mesozoic plutonic rocks are mapped primarily as granitic composition, and some age dates are available (Albers and Stewart, 1972). Mesozoic units mapped in the field as part of this research include quartz syenite, a quartz monzonite porphyry stock, quartz monzonite dikes, and a granite intrusion (Fig. 2) (Kruse, 1987b). These rocks are cut by narrow north-trending mineralized shear zones containing sericite (fine grained muscovite or illite) and iron oxide minerals (Wrucek

![Image](Image.png)

**Figure 1.** Sketch map showing location of the northern Grapevine Mountains (NGM) and Death Valley Sites.
et al., 1984; Kruse, 1987b). Slightly broader northwest-trending zones of disseminated quartz, pyrite, sericite, chalcopyrite, and fluorite mineralization (QSP alteration) ± goethite occur in the quartz monzonite porphyry (Fig. 3). This type of alteration is spatially associated with fine-grained quartz monzonite dikes (Kruse, 1987b). There are several small areas of quartz stockwork (silica flooding of the rocks) exposed at the surface in the center of the area. Skarn, composed mainly of brown andradite garnet intergrown with calcite, epidote, and tremolite, occurs around the perimeter of the quartz monzonite stock in Precambrian rocks. The NGM area has many of the characteristics common to porphyry copper deposits; however, there has not been any secondary (supergene) enrichment, and thus economic concentrations of ore do not occur. Complexly faulted, Tertiary
volcanic rocks related to the Timber Mountain Caldera in southern Nevada are abundant around the southern periphery of the study area and are overlain by volcaniclastic sedimentary rocks interbedded with rhyolite and basalt (Wruke et al., 1984). Quaternary deposits include Holocene and Pleistocene fanglomerates, pediment gravels, and alluvium; these have been mapped in reconnaissance (Moring, 1986), but no linked bedrock/surficial geology studies have been completed.

This article also presents preliminary results of mineralogical mapping using AVIRIS (Vane et al., 1993) in the Grapevine Mountains, proper, across northern Death Valley to Ubehebe Crater (Fig. 4). This region has not previously been mapped in detail, although maps and stratigraphic studies of portions of the area have been completed (Oakes, 1977; Wruke et al., 1984; Moring, 1986). The structure of the Grapevine Mountains is complex, and the section has been significantly thinned by extensive low-angle faulting (Wruke et al., 1984). Cambrian, Ordovician, and Mississippian carbonates with interbedded sandstones are the predominant rock types. Tertiary-age, gra-
nitric composition intrusions (Elliot et al., 1984) have altered the carbonates in some locations to serpentine (Oakes, 1977).

USE OF IMAGING SPECTROMETRY FOR GEOLOGIC MAPPING

General
Many naturally occurring materials can be identified and characterized based on their reflected-light spectral characteristics. In geology, the exact positions and shapes of visible and infrared absorption bands are different for different minerals, and reflectance spectra allow direct identification (Hunt and Salisbury, 1970; Hunt et al., 1971; Hunt, 1977; Lee and Raines, 1984; Clark et al., 1990; Grove et al., 1992).

Imaging spectrometers are remote sensing instruments that measure near-laboratory-quality spectra in narrow spectral bands with a corresponding spatial image for each band (Goetz et al.,
This makes possible direct identification of surface materials based on their spectral characteristics and presentation of the results as images. A complete spectrum for each picture element (pixel) can be derived from the data to allow quantification of physical parameters at the Earth's surface. Imaging spectrometry has been demonstrated as an effective tool for mapping surface mineralogy for a variety of geologic disciplines. It has been used in ore deposits (Goetz et al., 1985; Kruse, 1988; Hutsinpillar, 1988; Feldman and Taranik, 1988; Kruse et al., 1990a; Hook and Rast, 1990; Rubin, 1991), in petroleum geology (Dykstra and Segal, 1985; Lang, 1987) and for general geologic mapping (Mustard and Pieters, 1987; Carrere and Chadwick, 1990; Farrand and Singer, 1991; Clark et al., 1991; Kruse and Dietz, 1991; Boardman, 1993). While imaging spectrometry provides detailed maps of the spatial distribution of specific minerals, it does not produce geologic maps in the classical sense, but rather new information that can be added to that obtained through conventional geologic mapping to develop an improved understanding of the geology.

Prototype imaging spectrometer data from NASA's Airborne Imaging Spectrometer (AIS) (Vane et al., 1984; LaBaw, 1987) was previously used at the NGM site to help characterize and map hydrothermal alteration (Kruse, 1988). Signal-to-noise ratios (SNR) for these data ranged from 10/1 to 110/1 (depending on sensor configuration) at 2.2 μm for targets with 0.5 albedo (Vane and Goetz, 1988). Figure 5 provides a base-
line imaging spectrometer mineral map derived from multiple AIS flightlines to compare to the imaging spectrometer data discussed in detail in this article. These results summarize early efforts to code mineral absorption feature information as a three color composite image (Kruse, 1988). The principal problems with the AIS data were that they did not adequately cover the study area, had limited spectral coverage (1.2–2.4 μm), and often marginal signal-to-noise characteristics. Additionally, analysis software for extracting the spectral information was nonexistent. Despite the problems, it was apparent that these new data could provide valuable geologic information that could not be obtained from any other source. Thus, these and other early imaging spectrometer results in geology and other disciplines provided the basis for developing additional imaging spectrometer capabilities.

**AVIRIS Data and Initial Interactive Analysis**

The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) became operational in 1987. AVIRIS is the first of the second generation of imaging spectrometers measuring near-laboratory quality spectra in 224 10-nm-wide channels in the spectral range 0.41–2.45 μm (Porter and Enmark, 1987). The AVIRIS is flown aboard the NASA ER-2 aircraft at an altitude of 20 km, with an instantaneous field of view of 20 m, and a swath width of about 10 km. It utilizes four linear arrays and four individual spectrometers to collect data simultaneously for the 224 bands in a scanned 614 pixel-wide swath perpendicular to the aircraft direction. The second dimension of the images is provided by the forward motion of the aircraft, which moves the ground field of view along the terrain.

The AVIRIS data for the NGM site were obtained during May 1989 with signal-to-noise ratios of approximately 50/1 at 0.70 μm and 20/1 at 2.20 μm for targets with reflectances of 0.5 (Kruse, unpublished data). The area covered by these data is shown as area “1” on Figure 4 and consists of one AVIRIS segment (512 lines by 614 pixels). Additional AVIRIS data were acquired during September 1989 as part of the Geologic Remote Sensing Field Experiment (GRSFE) (Evans and Arvidson, 1990). The area covered by these data overlaps slightly with the May 1989

*Figure 6.* a) Mean AVIRIS radiance spectra for light (16 pixels) and dark (11 pixels) targets used in the empirical line calibration. Dark target is unaltered quartz syenite outcrop. Light target is unaltered volcanic tuff. The overall shape of the spectral curves is caused by the solar spectrum and atmospheric absorption. b) SIRIS reflectance spectra for light and dark targets used in the empirical line calibration are shown as “light.avi” and “dark.avi.” Polygon averages from the calibrated image for the same targets as Figure 6a are shown as “class 1 mean” (dark target) and “class 2 mean” (light target). Comparison of the two calibrated spectra to the radiance spectra in Figure 6a shows removal of the solar spectrum and some atmospheric effects. The close match in both overall brightness and in shape to the SIRIS spectra indicates successful forcing of the match between the image and the field spectra. Atmospheric absorption regions near 1.4 μm and 1.9 μm are masked out.
data and is shown as areas “2,” “3,” and “4” in Figure 4. Area 2 is approximately two and one-half AVIRIS scenes (1255 lines by 614 pixels). Analysis of areas 2 and 4 is ongoing. Area 3 is the subject of other analysis efforts (Kierein-Young and Kruse, 1991). Only areas 1 and 2 are discussed in this article.

The Spectral Image Processing System (SIPS) (Kruse et al., 1993) was used to preview the AVIRIS radiance images and to extract image radiance spectra for calibration (Fig. 6a). The data were calibrated to apparent reflectance using ground targets and the empirical line method (Ballew, 1975; Roberts et al., 1985; Kruse et al., 1990b). Field spectra measured with the Single Beam Infrared Intelligent Spectrometer (SIRIS) (GER, 1988) were used as the calibration spectra (Fig. 6b). The empirical line correction uses a gain and offset calculated for each band by determining the best least-squares fit between the sets of field spectra and the corresponding image spectrum characterizing the same ground area. The result of this calibration is an approximation of reflectance (apparent reflectance). Most atmospheric, viewing geometry, and instrument artifacts are removed by the calibration; however, there may be some residual atmospheric effects caused by elevation variation within the AVIRIS scene.

Once the data are calibrated to reflectance, interactive analysis using SIPS was used to determine the principal minerals at the surface. In semiarid terrains, this can consist of procedures
as simple as making the correct color composite images. A false color composite using Bands 28, 17, and 10 (0.66 \( \mu \text{m} \), 0.55 \( \mu \text{m} \) and 0.48 \( \mu \text{m} \)) as RGB simulates a color infrared (CIR) photograph and makes a good starting point (Fig. 7). By using specific image bands that record reflected light at wavelengths affected by specific minerals, it is possible to construct a color composite that shows the spatial distribution of minerals having specific absorption features. For example, in the Band 28, 210, 10 (0.66 \( \mu \text{m} \), 2.31 \( \mu \text{m} \), 0.48 \( \mu \text{m} \)) (RGB) color composite shown in Figure 8, the distribution of carbonates is shown in magenta, corresponding to low reflectance in Band 210 caused by CO\(_3^−\) absorption near 2.3 \( \mu \text{m} \) in carbonates. Other minerals having similar absorption bands will appear in similar colors.

After color composites showing the distribution of minerals are made, extraction of average spectra from areas with spectral character allows comparison to library spectra of specific minerals for identification. For example, areas appearing yellow-brown on the CIR image (Fig. 7) correspond to occurrences of goethite, while those appearing red-brown on the same image correspond to hematite (Fig. 9). Browsing of spectra in the carbonate area shown on Figure 8 allows identification of calcite and dolomite (Fig. 10). It is impossible, however, to interactively view and analyze each spectrum in an imaging spectrometer data set. Thus we must extract image spectra characteristic of the principal pure materials on the ground or “endmember spectra” and develop automated techniques to identify and characterize these ma-
materials in the entire image cube. Figure 11 shows complete endmember spectra extracted from the NGM image data for the main mineral groups in this area. These spectra are used for spectral unmixing discussed later in this article.

Binary Encoding

A simple, commonly used (and surprisingly effective) method for analysis of imaging spectrometer data involves binary encoding and spectral matching using a reference library (Mazer et al., 1988). Each reference spectrum is encoded by finding its mean and determining whether each point in the spectrum is above or below the mean. The spectrum is stored as an integer value with each bit representing a point in the spectrum. If a point is above or equal to the mean, it is set to 1, and if a point is below the mean, it is set to 0. The spectrum for each pixel in the image is encoded in the same manner and compared to the reference spectrum to determine points where the encoded spectra match. Binary encoding is a fast and accurate technique for identifying minerals with distinct absorption bands because it is sensitive to band positions and insensitive to albedo (brightness) variations. Additionally, it is not very sensi-

Figure 9. a) AVIRIS apparent reflectance spectra for the minerals goethite and hematite. b) Laboratory reflectance spectra convolved to AVIRIS bands for the minerals goethite and hematite.

Figure 10. The spectrum labeled "class 1—mean" is for an area on the ground consisting primarily of dolomite (48 pixels). Spectrum NDV9117B.PMC is a field spectrum acquired using a prototype high spectral resolution field spectrometer (PIMA II, Integrated Spectronics Inc., Sydney, Australia) of an outcrop in the same area. The spectrum labeled "class 2—mean" is for an area on the ground consisting primarily of calcite (35 pixels). Spectrum NGM919C.PMC is a field spectrum of an outcrop in the same area. Note the relative positions of the major absorption feature at 2.32 μm for dolomite and at 2.34 μm for calcite and the correspondence in position and shapes of the features in the field spectra to those in the AVIRIS data.
tive to high frequency noise in the data. Previous investigations have used a simple tolerance to determine how many points in the spectra must match in order to classify that pixel as being a match to the reference (Mazer, 1988; Kruse et al., 1990a). Based on experience with a number of imaging spectrometer data sets, determination of a "percentage match" was used in this study. The resulting image, rather than being a binary "on" or "off" image, is a gray-scale image in which brightness is proportional to the degree of match between the image spectrum and the library spectrum (Fig. 12).

For the NGM AVIRIS data the binary encoding technique was used to find the distribution of five minerals identified in the region through interactive analysis of the images in SIPS and represented by the endmember library in Figures 11. Laboratory spectra for calcite, dolomite, illite (sericite), hematite, and goethite were used as references for the classification. The 2.0–2.4 μm region was selectively used for the carbonates and sericite, while the 0.4–1.0 μm range was used for the iron oxide minerals. These regions were chosen for encoding because of observed diagnostic spectral characteristics limited to these wavelength ranges of the spectrum. This method is more effective than using the entire spectrum and allows determination of areas of overlap where minerals have only unique visible or unique infrared absorption features (e.g., mixtures of sericite and goethite). Figure 12 shows a good match to known mineralogy in the area (Fig. 3) (Kruse, 1987b).

**Expert System Analysis**

Because of the large volume of data that is generated by imaging spectrometers and its unique spectral/spatial nature, development of automated data reduction and analysis capabilities is required to allow extraction of useful information. Techniques for extraction of spectral features from field and laboratory reflectance spectra for geologic applications have been in use for several years (Green and Craig, 1985; Kruse et al., 1985; 1986; Yamaguchi and Lyon, 1986; Clark et al., 1987). Only recently have attempts been made to apply these techniques to imaging spectrometer data (Kruse et al., 1988; Kruse, 1987a, 1988; Clark et al., 1991; Abrams and Hook, 1991).

As part of the research described here, an expert system was developed that allowed auto-
Figure 12. Image mosaic of binary encoding results. The upper left image is AVIRIS Band 28 (0.66 μm) with topographic contour overlay. Gray-scale images show the degree of binary match. Brighter areas in these images represent a higher degree of binary match to the library minerals. 1) Top center, calcite; 2) top right, dolomite; 3) lower left, sericite; 4) lower center, hematite; 5) lower right, goethite.
Table 1. List of Minerals and Other Materials Used in the Expert System

<table>
<thead>
<tr>
<th>Sample ID</th>
<th>Mineral</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AL705 K-alunite</td>
</tr>
<tr>
<td>2</td>
<td>AL706 Na-alunite</td>
</tr>
<tr>
<td>3</td>
<td>AM3000 Actinolite</td>
</tr>
<tr>
<td>4</td>
<td>AMT3001 Tremolite</td>
</tr>
<tr>
<td>5</td>
<td>CH2402 Chlorite</td>
</tr>
<tr>
<td>6</td>
<td>CO2004 Calcite</td>
</tr>
<tr>
<td>7</td>
<td>COD2005 Dolomite</td>
</tr>
<tr>
<td>8</td>
<td>COS2002 Siderite</td>
</tr>
<tr>
<td>9</td>
<td>FE2600 Goethite</td>
</tr>
<tr>
<td>10</td>
<td>FE2602 Hematite</td>
</tr>
<tr>
<td>11</td>
<td>IL101 2M-ilbite</td>
</tr>
<tr>
<td>12</td>
<td>IL105 1M-ilbite</td>
</tr>
<tr>
<td>13</td>
<td>IL107 Muscovite</td>
</tr>
<tr>
<td>14</td>
<td>IS200 Illite / smectite</td>
</tr>
<tr>
<td>15</td>
<td>JR2501 Jarosite</td>
</tr>
<tr>
<td>16</td>
<td>KL500 Well crystalline kaolinite</td>
</tr>
<tr>
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<td>SU2202 Gypsum</td>
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<td>25</td>
<td>TL2702 Talc</td>
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</table>

26 Green vegetation
27 Dry vegetation

Automated identification of Earth surface materials based on their spectral characteristics in imaging spectrometer data (Kruse, 1990b). A spectral library of laboratory spectral reflectance measurements was used to develop a generalized knowledge base for analysis of visible and infrared reflectance spectra. Spectral features were digitally extracted from a spectral library containing a suite of 25 common minerals (Kruse, unpublished data) and both green and dry vegetation (Table 1). Numerical analysis and characterization of the digital reflectance measurements were used to establish quantitative criteria for identifying minerals, mineral mixtures, and vegetation.

The absorption feature information was extracted from each laboratory spectrum using the following automated techniques (Kruse et al., 1988; 1990b).

1. A continuum was defined for each spectrum by finding the high points (local maxima) and fitting straight line segments between these points. Figure 13a shows a fitted continuum for a laboratory calcite spectrum.

2. The continuum was divided into the original spectrum to normalize the absorption bands to a common reference (Fig. 13b). [See Clark and Roush (1984) for a discussion of
division versus subtraction of the continuum.]
3. The minima of the continuum-removed spectrum were determined and the 10 strongest absorption features extracted (Figure 13b).
4. The wavelength position, depth, full width at half the maximum depth (FWHM), and asymmetry for each of these 10 features were determined and tabulated (Figs. 13b and 13c). The asymmetry was 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 (Fig. 13c). The base 10 logarithm was 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 that are 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 was then interactively reviewed simultaneously in both tabular and graphical format to determine if features extracted from the digital spectra were representative of the material measured or were due to impurities. The four parameters derived using the feature extraction procedure were 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 were 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 were used to analyze each unknown spectrum. The spectral library itself was never accessed during the expert system analysis. The strongest absorption feature for a given spectrum was determined, and used to broadly classify the spectrum (e.g., clay, carbonate, iron oxide). Initially, for individual spectra, a tree hierarchy was used to model the spectral analysis procedures and decision processes followed by an experienced analyst. Primary band

**1st Decision** (Surface class)
- if not sharp spectral band near 0.68
  - then look for in rock class

**2nd Decision** (rock level)
- if it has a deep band in 2.30 - 2.35 µm region
  - then look for in "carbonate" species.

**3rd Decision** ("carbonate" species)
- if the strongest absorption feature is a single band near 2.34 µm
  - then it is calcite

**else if** the strongest absorption feature is a single band near 2.32 µm
  - then it is dolomite.

*Figure 14.* Generalized example of rules for expert system analysis of calcite and dolomite.

*Figure 15.* Flow diagram showing procedures for analysis of reflectance spectra using the expert system (including binary encoding).
characteristics and secondary/tertiary absorption bands were used to progress through the tree structure until an identification was made. Figure 14 shows an example of generalized rules for identification of calcite and dolomite laboratory spectra. 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.

The expert system was tested on selected laboratory mineral spectra and field spectra of rocks using the continuum-removal and feature extraction algorithms and the basic set of rules derived from the analysis. The laboratory reflectance spectra were also convolved with random noise to test the possibilities of success on aircraft spectra with various noise characteristics. Because identification was very adversely affected by low signal-to-noise ratios (similar to those expected with aircraft data), the binary encoding algorithm (Mazer et al., 1988) was included as part of the expert system to reduce noise sensitivity. Ideally, the expert system would use only the feature information; however, the modeling with the laboratory spectra with introduced noise shows that SNRs of approximately 50/1 or better are required to achieve success rates of 95% (Kruse, unpublished data). Figure 15 shows a flow diagram of the analysis procedures. Note that the feature extraction and binary encoding procedures operate independently to select material candidates. Features matching specific rules are given greater weight than binary matches in the final decision; however, in noisy data, the binary encoding has a significant effect on the decision process.

Figure 16 shows the results of analysis of the calcite spectrum shown in Figure 13 using the expert system. The results of the feature extraction procedure are shown in Figure 16a. The interaction of the absorption features and the rules result in the broad classification shown in Figure 16b. Figure 16c shows the percentage match of the spectrum with the binary library. Note the 100% match between the library calcite and the unknown spectrum. This is because the calcite spectrum comes from the library. Figure 16d shows the final result of the decision process when the binary encoding is used to weight the feature extraction process. Figures 16e and 16f show the justification for the identification of calcite versus dolomite.

The final test of the expert system was the analysis of the AVIRIS data to automatically identify minerals and to map the spatial distributions. The absorption feature positions and shapes of each reflectance spectrum for each picture element (pixel) were characterized using the automated techniques described previously for individual laboratory spectra. In actual application of the expert system to the AVIRIS images, it was necessary to change the definition of facts and rules using the spectral features to a more quantitative form to produce probability images. In practice, rather than using a hierarchical tree, the features attributed to a specific mineral were assigned weighting factors between 0 and 1 depending upon whether they were required to identify the mineral (must-have, weight = 1), were likely to occur in the specific mineral (should-have, weight = 0.6), or might be present (may-have, weight = 0.3). The weights chosen were arbitrary and have no direct physical meaning. The features found in a particular pixel were then compared to the expected features for each spectrum in the library. For example, if a specific mineral was expected to have three absorption features with respective weights of 1.0, 0.6, and 0.3 (must-have, should-have, and may-have) and it only had two of the features (say the 1.0 and the 0.3 features), then the probability of occurrence of that specific mineral could be represented as \((1.0 + 0.3)/(1.0 + 0.6 + 0.3) = 0.68\). Figure 17 shows the results of the expert system analysis of the AVIRIS image using only the absorption feature analysis. To help deal with some of the noise in the AVIRIS data, the results of the spectral features analysis were then assigned a weight of 0.67 in the final decision images while the results of the binary encoding procedure were assigned a weight of 0.33. 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 10 strongest absorption features, and an “analysis cube” showing the location and probability of occurrence of the 25 minerals.
16A. FEATURE ANALYSIS:

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16B. EXPERT SYSTEM BROAD CLASSIFICATION:

There are features from:
- vegetation
- carbonates
- clays
- micas and illites
- calcite

16C. BINARY ENCODING MATCHES (percentage):

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<td>Alunite</td>
<td>74.76</td>
</tr>
<tr>
<td>Epidote</td>
<td>53.81</td>
</tr>
<tr>
<td>Calcite</td>
<td>100.00</td>
</tr>
<tr>
<td>Actinolite</td>
<td>52.38</td>
</tr>
<tr>
<td>Jarosite</td>
<td>58.10</td>
</tr>
<tr>
<td>Goethite</td>
<td>56.67</td>
</tr>
<tr>
<td>Dry Grass</td>
<td>73.33</td>
</tr>
</tbody>
</table>

16D. CALCITE FINAL RESULTS - WEIGHTED DECISION:

According to the expert system and the binary encoding performed on the spectrum, the probability of the presence of:

- Calcite is nearly certain
- Dolomite is medium
- Buddingtonite is medium
- Muscovite is medium

16E. JUSTIFICATION - CALCITE:

The binary match to calcite is 100.00 % so the binary match is rated very high
The carbonate feature between 2.30 and 2.35 μm is present
The calcite feature at 2.34 μm is present
The overall expert guess for the probability of calcite is Nearly Certain

16F. JUSTIFICATION - DOLOMITE:

The binary match to dolomite is 86.19 % so the binary match is rated high
The carbonate feature between 2.30 and 2.35 μm is present
The dolomite feature at 2.32 μm is not present
The overall expert guess for the probability of dolomite is Medium

*Figure 16. Example of expert system decision process for calcite vs. dolomite.*
Figure 17. Image mosaic of expert system analysis results using facts and rules based only on absorption features (no binary encoding). The upper left image is AVIRIS Band 28 (0.66 μm) with topographic contour overlay. Gray-scale images show the probability distributions of specific minerals. 1) Top center, calcite; 2) top right, dolomite; 3) lower left, sericite; 4) lower center, hematite; 5) lower right, goethite. Brighter areas in these images represent a higher probability of occurrence of each mineral.
Figure 18. Image mosaic of expert system analysis results using facts and rules based on absorption features combined with binary encoding. The upper left image is an AVHRR CHR color composite image (Bands 28, 17, and 10 in RGB) with topographic contour overlay. Density-sliced images show the probability distributions of specific minerals. Images are density-sliced from 0 to 1 probability with purples, greens, yellows, and oranges representing progressively higher probabilities. Specifics are caused by noise, which affects the feature extraction procedure. 1) Top center, calcite; 2) top right, dolomite; 3) lower left, sericite; 4) lower center, hematite; 5) lower right, goethite.
and both dry and green vegetation based on the weighted combination of binary encoding, and feature analysis in the expert system. The analysis cube also contains four images that help with evaluation of the expert system mapping success. These are 1) the “final decision best endmember” image showing the single best match for each pixel, 2) the “sum of decisions” image showing the sum of all probabilities for each pixel, 3) the “number of decisions greater than or equal to 50%” image showing those areas with endmembers with high probabilities, and 4) the “no match” image showing those areas with maximum probabilities less than or equal to 10%.

Interactive display and analyses of the 27 probability images and the additional images described above using SIPS permitted determination of the spatial extent of specific minerals and identification of problem areas where the expert system may have identified multiple minerals, or no minerals at all. Figure 18 shows selected image planes from the analysis cube. Images have been density sliced to show the probability of occurrence of the specific minerals. Of the 27 possible probability images, only those five images with the highest probabilities are shown. These images formed the starting point for detailed analyses.

While this application of the expert system for analysis of imaging spectrometer data is for a geologic site in a semiarid area of well-exposed mineralogy, there is no reason to believe that it cannot be used to some extent in more temperate, somewhat more vegetated areas to identify endmembers and map their distribution. The feature extraction procedures have been tested on individual vegetation spectra to determine vegetation stress with excellent results, and could potentially be used to map vegetation characteristics using imaging spectrometers (Singhroy and Kruse, 1991).

**Spectral Unmixing**

Spectral classification programs such as binary encoding or the expert system described above are only the first step in mineral mapping using imaging spectrometer data because natural surfaces are rarely composed of a single uniform material. Geologic surfaces are more commonly made up of mixtures or assemblages of fine-grained, intimately mixed, minerals; alteration products; or weathered constituents. Spectral mixing is a consequence of the mixing of materials having different spectral properties within the GFOV of a single image pixel. Several researchers have investigated mixing scales and linearity. Singer and McCord (1979) found that if the scale of the mixing is large (macroscopic), then the mixing occurs in a linear fashion. For microscopic or intimate mixtures, the mixing is generally nonlinear (Nash and Conel, 1974; Singer, 1981).

Boardman (1989; 1993) addressed the macroscopic mixing problem using singular value matrix decomposition (SVD) to determine the scale of spatial mixing and to linearly unmix AVIRIS data. This technique assumes that most mixing is on the macroscopic scale, and thus linear. It is recognized that for most geologic situations there is a significant amount of intimate mixing, and therefore the linear unmixing techniques are at best an approximation. Grain-size differences are also not taken into account by the linear methods. Abundances determined using these techniques are not as accurate as those determined using nonlinear techniques; however, to the first order, they appear to adequately represent the geologic conditions at the surface.

A spectral library forms the initial data matrix for the analysis. Selection of the ideal spectral library consists of definition of endmembers that when linearly combined can form all other spectra. An inverse of the original spectral library matrix is then formed by multiplying together the transposes of the orthogonal matrices and the reciprocal values of the diagonal matrix (Boardman, 1989). A simple vector-matrix multiplication between the inverse library matrix and an observed mixed spectrum gives an estimate of the abundance of the library endmembers for the unknown spectrum.

Linear spectral unmixing was applied to the NGM AVIRIS data using the endmember spectra presented in Figure 11 for calcite, dolomite, sericite, hematite, and goethite. The data were first examined using unconstrained unmixing in which the derived abundances were free to take on any value including negative ones. The output of the unmixing process was an image data cube with the same spatial dimensions as the input data; five spatial output bands represent the abundances of the five endmembers. The analysis also produced
Figure 19. Image mosaic of linear spectral unmixing results. The upper left image is AVIRIS Band 28 (0.66 μm) with topographic contour overlay. Gray-scale images show the endmember mineral abundances. Brighter areas in these images represent higher abundances. 1) Top center, calcite; 2) top right, dolomite; 3) lower left, sericite; 4) lower center, hematite; 5) lower right, goethite.
two additional images, one showing the sum of the abundances at each pixel and the other the root-mean-square (rms) error values at each pixel. The unconstrained unmixing runs on a full AVIRIS segment in less than an hour (on a 30 MIPS-class machine) and provided a rapid means of evaluating mineral abundances and endmember library validity. Interactive analysis of the abundance cube, the sum image, and the rms error image indicated that this library explained most of the spectral variation in the NGM AVIRIS data. A second iteration of unmixing using the same library but with results constrained to be nonnegative and to sum to one or less (100%) was used to derive quantitative mineral abundances. This analysis takes approximately 6 h for a single AVIRIS frame using a five-endmember library. Because image spectra were used as endmembers, and the “hematite” and “goethite” endmembers actually contain spectral features for sericite in the 2.0–2.45 \( \mu \text{m} \) range, the results for these two minerals are actually the abundances for mixed hematite/sericite or goethite/sericite. Figure 19 shows the results of the constrained unmixing with brighter pixels representing higher abundances.

**Discussion of Results**

The techniques described above form one comprehensive approach to analysis of the AVIRIS data and imaging spectrometer data in general. Calibration to reflectance is a required preprocessing step. Accurate calibration is a prerequisite for all analytical methods presented here. Presently available calibration methods that do not require ancillary data include the flat field method (Goetz et al., 1985), the Internal Average Relative Reflectance (IARR) calibration (Kruse, 1988) or logarithmic residuals (Green and Craig, 1985), and use of atmospheric models (Gao and Goetz, 1990; Green, 1991). The method used in this study, the empirical line calibration, requires field spectral measurements.

Given calibrated data, interactive analysis using SIPS and automated analysis using the expert system described above can be used to produce a preliminary mineral map for 27 endmembers in less than 1 h for a standard 614 line by 512 pixel AVIRIS scene (on a 30 MIPS-class computer). Determination of mineral abundances is presently more time-consuming, requiring 1 h or more to perform unconstrained unmixing and up to about 10 h to do a fully constrained unmixing with 10 endmembers.

In this study, the feature extraction procedures and the expert system were successfully used to analyze lab and field spectra of unknown materials. The expert system also successfully identified minerals using the 224 channel AVIRIS data. The 1989 AVIRIS data allowed not only identification of groups of minerals such as clays, iron oxides, and carbonates, but permitted identification of the individual species. Calcite and dolomite were identified based upon a 20 nm (two-channel) difference between the position of the main absorption feature (2.34 \( \mu \text{m} \) vs. 2.32 \( \mu \text{m} \)) and shifts in the positions of ancillary features near 2.15 \( \mu \text{m} \), 1.98 \( \mu \text{m} \), and 1.88 \( \mu \text{m} \). The feature extraction procedures successfully produced continuum-removed spectra that show these offsets. Goethite and hematite were identified using the AVIRIS data based on the presence of a broad absorption feature near 0.9 \( \mu \text{m} \) for goethite and 0.85 \( \mu \text{m} \) for hematite, and the visible absorption shoulder near 0.48 \( \mu \text{m} \) for goethite and near 0.58 \( \mu \text{m} \) for hematite. Sericite (fine-grained muscovite or well crystalline illite) was identified based upon a symmetrical absorption feature near 2.21 \( \mu \text{m} \) and a secondary absorption feature near 2.35 \( \mu \text{m} \). While, in the past, this mineral has often been confused with other similar minerals such as montmorillonite (smectite), it is easily identified and mapped when the characteristics of multiple absorption features are used simultaneously in the expert system. Spot checking of the imaging spectrometer data for areas of known mineralogy shows a good match between extracted absorption features, laboratory measurements, and the expert system's automated identifications.

Endmember spectra derived through interactive analysis and from the results of the expert system analysis were used to perform linear spectral unmixing. This technique produced images that clearly defined the known distributions and abundances (and additional previously unmapped concentrations) of the carbonates, iron oxides, and sericite. Figure 19 shows a “donut”-shaped concentration of carbonate minerals in the southeast corner of the NGM image. The unmixing of calcite and dolomite indicates the dominant mineralogy of the center of the donut is calcite,
while the exterior ring consists primarily of dolomite. It is also clear from this image that mapping either of these distributions as a single mineral is an oversimplification. Most occurrences of these two minerals consist of mixtures of both minerals. Field mapping guided by the mineralogy determined from the AVIRIS image indicates that this area is a large, folded roof pendant of Precambrian
carbonates. Figure 20 is a generalized compilation and interpretation of spectral mineralogy from the expert system and spectral unmixing. It was derived by visual interpretation of all of the previous images using a clear overlay and by interactive extraction of spectra from the image cubes. Because it has been generalized, small areas that may have showed varying mineralogy from image to image due to misclassification (caused predominately by noisy data) have been absorbed into larger areas based upon visual inspection of reflectance spectra and manual comparison to the spectral library. Note the northwest-trending linear alignment of sericite + goethite concentrations. By comparison with Figures 2 and 3, it can be seen that goethite is limited to alteration in Jurassic intrusive rocks, while hematite is primarily associated with Tertiary volcanic rocks. The expert system and linear spectral unmixing results also provided additional information about mineral abundances and unmapped occurrences of minerals that will require further field checking.

The expert system and spectral unmixing were also run on the GRSFE AVIRIS data in the Grapevine Mountains, proper. The resulting mineral maps provided the basis for reconnaissance geologic mapping (Fig. 21). In the one area of overlap with the NGM site (at the northern end of the flightline), there is good agreement in the mineral identifications between the two flightlines. Minerals identified in this area include calcite, dolomite, goethite, hematite, and sericite. The middle one third of the GRSFE AVIRIS flightline consists primarily of Tertiary volcanic rocks (Wrucke et al., 1984). This area is dominated in the AVIRIS data by the mineral hematite, likely the result of surface weathering of mafic minerals in the volcanic rocks. The expert system also identified occurrences of montmorillonite and jarosite in this region. One possible explanation for the montmorillonite concentrations, which appear oval in shape, is that they are associated with small intrusions. This still requires field verification. The southern one third of this area is dominated by Paleozoic sediments (Wrucke et al., 1984). Detailed examination of the AVIRIS image spectra combined with the expert system, unmixing, and photointerpretation were used to subdivide these rocks into several different classes. The most obvious of these are the nearly pure dolomite (D1) and pure calcite (C1). Note also the distribution of alluvial fans derived from the main dolomite unit (DF1). The general accuracy of these classifications has been confirmed by both field and laboratory spectral measurements (Kruse, unpublished data); however, further field checks and mapping are pending. The "U-shaped" map pattern of unit CFe1 in Figure 21b indicates probable folding, while truncation of this and other units on the southeast side likely represents faulting of the folded section. Comparison of this figure to existing maps (Oakes, 1977) and field reconnaissance indicates that the Grapevine Moun-
Figure 21b. Generalized AVIRIS mineral map produced for the segments shown in Figure 21a using the expert system, spectral unmixing, and photointerpretation. Field reconnaissance mapping and spot measurements with a field spectrometer have validated the basic distribution of most minerals; however, more field mapping is planned.

tains take the form of a large, faulted anticline. Unit D1 corresponds to recrystallized dolomite contact metamorphosed by a Tertiary-age intrusion (Oakes, 1977). Field reconnaissance also indicates that unit C1 corresponds to the distribution of travertine at fault-controlled springs at the "Lower Grapevine Ranch" area within Death Valley National Monument. This area is presently closed to the public. The areas of vegetation shown in Figure 21b correspond to lush green vegetation along the active springs. Several additional dolomite and calcite and mixed carbonate/iron oxide units were defined based on their spectral signatures in the AVIRIS data. Verification of these units and integration with structural information will require additional field mapping. Examination of unmixing error images for the entire two and one-half AVIRIS scenes covering this area indicated that additional minerals were present beyond those described above and included in the unmixing library. Interactive analyses of the areas with high error in the AVIRIS unmixing indicated that these minerals corresponded to occurrences of zeolites and to Tertiary basalts.
CONCLUSIONS

An expert system has been developed that allows automated identification of Earth surface materials based on their spectral characteristics in imaging spectrometer data. Automated, techniques were developed for the extraction and characterization of absorption features by analyzing a suite of laboratory spectra of some of the most common minerals. Critical absorption band characteristics for identification were defined, and these were used to develop facts and rules defining a generalized knowledge base for analysis of reflectance spectra that allowed the computer to make decisions similar to those that would be made by an experienced analyst. The expert system produced image maps from AVIRIS data showing the predominant surface mineralogy. Linear spectral unmixing was used to refine the mineral maps, map mineral assemblages, and to determine mineral abundances.

At the northern Grapevine Mountains site, several distinct alteration minerals were identified and mapped using the AVIRIS data. Northwest-trending quartz-sericite-pyrite (QSP) alteration predominates and is spatially associated with quartz monzonite dikes. The extent of the alteration indicates that there may be a larger quartz monzonite body at depth. Alteration occurs as up to 50-m-wide zones of northwest-trending, sericitized, goethite-stained quartz monzonite porphyry surrounded by broader halos (up to 100 m wide total) of less intense sericite alteration without goethite. A goethitic alteration zone occurs in quartz syenite, and is also spatially associated with a granitic intrusion along the eastern edge of the main quartz monzonite intrusion. Roof pendants of Precambrian rocks containing calcite and dolomite are complexly folded; the AVIRIS data simplified identification and mapping of these folds. Subparallelism of alteration, veins, dikes, and faults at the NGM site may indicate deep-seated crustal weaknesses persistent over long periods of time that have controlled emplacement of the plutons, alteration, and subsequent faulting.

South of the NGM site, hematite is the dominant iron oxide, exposed primarily in Tertiary volcanic rocks related to the Timber Mountain Caldera. Within the volcanic section, however, there are several circular areas with concentra-

tions of sericite, montmorillonite, and jarosite that may correspond to previously unmapped Tertiary-age intrusives. Mineral maps of the Grapevine Mountains, proper, show complexly folded and faulted dolomites and limestones with varying degrees of iron oxide staining. The AVIRIS data are playing a major role in mapping the carbonate lithologies, and, in conjunction with field mapping, in determining their spatial relation to faulting. The AVIRIS data also showed the distribution of vegetation along the east side of Death Valley which was clearly limited to springs associated with faults. Calcite was mapped adjacent to these springs using the AVIRIS data and later verified as travertine deposits through field reconnaissance.

Geographically referenced image-maps produced from the AVIRIS data are being transferred directly into the ARC/INFO Geographic Information System (GIS) to produce new base maps for improved interpretation of the geologic processes shaping the present land surface. These maps contain new information that is complementary to that obtained through conventional geologic mapping. When used in conjunction with other geologic maps, geophysics, geochemistry, and other remote sensing data sets, they permit improved geologic mapping and interpretation, even in areas that are thought to be well understood and well mapped.

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