A Spectral-Feature-Based Expert System for Analysis of Reflectance Spectra and Hyperspectral Data

Description: A generalized expert system the “Spectral Expert” has been implemented for identification of earth-surface materials based on extraction of key spectral features from Visible/Near Infrared and Short Wave Infrared reflectance spectra and hyperspectral imagery (HSI).
Abstract
A generalized expert system has been implemented for identification of materials based on extraction of key spectral features from visible/near infrared (VNIR) and shortwave infrared (SWIR) reflectance spectra and hyperspectral imagery (HSI). A spectral library containing materials of interest is first automatically analyzed to extract and characterize absorption features. An expert then optionally analyzes facts and rules built in the first step to refine key feature definitions and parameterization. A series of similar spectra can also be used to establish spectral variability and rule tolerances. The rules can be used by a non-expert to identify materials using individual reflectance spectra, or for the analysis of HSI data. The result for a single spectrum is a score between 0.0 and 1.0 for each specific material in the spectral library or for hyperspectral data, a classified image showing the predominate material on a per-pixel basis and a score image for each material.

Introduction
Hyperspectral Data
Hyperspectral Imagery (HSI) data consist of 2-d image data with a large number of spatially contiguous spectral bands (Goetz et al., 1985). These data are unique because they allow extraction of a high-quality spectral signature from each pixel of the imagery (Figure 1). HSI data can be analyzed both spatially and spectrally (Goetz et al., 1985, Rowan et al., 2003). Instrumentation has evolved over the last 25 years, with both airborne and satellite sensors available (Green et al., 1998; Pearlman et al., 1999). The sensor used for this study, the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) is flown by NASA/JPL on a variety of aircraft at spatial resolutions ranging from 2 – 20 meters. AVIRIS is a 224-channel imaging spectrometer with approximately 10 nm spectral resolution covering the 0.4 – 2.5 micrometer spectral range [Porter and Enmark 1987; Green et al., 1998]. The sensor is a whiskbroom system utilizing scanning foreoptics to acquire cross-track data. The IFOV is 1 milliradian. Four off-axis double-pass Schmidt spectrometers receive incoming illumination from the foreoptics using optical fibers. Four linear arrays, one for each spectrometer, provide high sensitivity in the 0.4 to 0.7 micrometer, 0.7 to 1.2 micrometer, 1.2 to 1.8 micrometer, and 1.8 to 2.5 micrometer regions respectively. AVIRIS has operated for over 20 years, with numerous technology upgrades to insure optimum performance (Green et al., 1998).
Identification of Materials using Spectroscopy

Many Earth-Surface materials have diagnostic spectral absorption features in the Visible/Near-Infrared (VNIR) and Short-Wave Infrared (SWIR) that should allow unique identification and mapping using reflectance spectroscopy and hyperspectral imaging (Hunt, 1977; Clark et al., 1990b, 1993, 2003b). Feature-based hyperspectral data analysis methods using spectral libraries of common materials (mostly minerals) have been in use for over 25 years (Goetz et al., 1985; Yamaguchi and Lyon, 1986; Kruse et al, 1985, 1993a, 1999, 2003; Kruse, 1988, 1995; Baugh et al., 1998; Clark et al., 1987, 1990a, 1991, 1992a, 2003a). These methods until now have not achieved their full potential, however, mostly because they require extensive interaction by an expert with the spectral library to determine diagnostic features. In addition, feature-based methods typically do not take spectral mixing or variability into account, and thus work only for certain materials under narrow conditions. Extrapolation to different times, places, materials, and hyperspectral datasets is difficult. The research described here was designed to minimize the requirement for a spectroscopy expert and expedite analysis of new spectral datasets by
automatically building feature-based rules from reflectance spectral libraries, taking into account spectral variability. A non-expert can use our approach, the “Spectral Expert®” to analyze any spectral library to automatically produce rules for identification of unknown materials using their spectral properties. Spectral feature information thus extracted can then be used to analyze and identify unknown field spectra or laboratory spectra, or for analysis of hyperspectral datasets. This paper describes the methods used and shows some examples illustrating spectral-feature-based identification and mapping results.

**Methods**

**Basic Approach**

The Spectral Expert builds on and refines previous concepts for spectral-feature-based analysis of geologic and military datasets (Kruse and Lefkoff, 1993, 1999; Boardman and Kruse, 1994; Kruse et al., 1993; Clark et al., 2003a). The core approach is to extract and isolate individual reflectance absorption features, to characterize these features using objective parameters, to automatically build rules describing the spectral features, and to identify unknown materials by matching their absorption features to the previously defined rules. A spectral library of known materials is used as the starting point. A “continuum” is defined for each spectrum in the library by finding the high points (local maxima) and fitting straight line segments between these points (Clark and Roush, 1984, Kruse and Lefkoff, 1993) (Figure 2, left). The continuum-removal process is fully automated. For illustration purposes only in the figure, the original reflectance spectrum is plotted as a dotted line. The continuum is plotted as a solid line over the top of the reflectance spectrum. The continuum is divided into the original spectrum to normalize the absorption bands to a common reference. This allows us to concentrate on the individual spectral features rather than the overall spectral shape. Individual absorption features are extracted from the continuum-removed spectra and analyzed to determine key parameters, including their continuum start and end points, continuum slope, and continuum brightness for each feature (Figure 2, left). Other parameters extracted include the wavelength position of the feature, the feature depth, the full width at half the maximum depth (FWHM), and absorption band asymmetry (Kruse and Lefkoff, 1999) (Figure 2 right, Figure 3). Again, the process is fully automated.

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Figure 2: Left: Fitted continuum and selected absorption band parameters. Right: Continuum removed spectrum and selected extracted band parameters.

Asymmetric Left    Symmetric    Asymmetric Right

Negative    Zero    Positive

Figure 3: Spectral Feature Parameters – Band Asymmetry is defined as the base 10 logarithm of the area to the right of the band center divided by the area to the left of the band center. Symmetrical absorption bands have an asymmetry of zero, those with left asymmetry are negative and those with right asymmetry are positive (Kruse and Lefkoff, 1999).
Building Facts and Rules

A reference spectral library is obtained, either from laboratory measurements, field spectral measurements, or by extracting key spectra from HSI data. Each spectrum in the library is automatically analyzed by removing the continuum, extracting the features, and calculating the absorption band parameters described above. The results are saved in a “fact” file, which contains all band parameter information (Kruse and Lefkoff, 1993). The all-inclusive facts are automatically reduced to “key” facts using a series of user-selectable tolerances designed to reduce spurious features caused by spectrum noise. These include tolerances for the number of features (and sub-features), acceptable minimum feature depth, and proximity of adjacent features. Default tolerances that produce reasonable results with typical reflectance spectra are designed into the system. The reduced fact set becomes the expert system “rule” file. The analyst also has the option of changing the tolerances and/or interactively reviewing and editing the rules to modify rule parameters and tolerances (Figure 4).

Figure 4: The Spectral Expert progression from “Facts” to “Rules”. Left: Spectral plot showing all of the features extracted using the automated process. Features are marked with arrows. These are the Facts. See Table 1 for feature detail. Right: Spectral plot showing the features retained after using default tolerances to automatically remove small (~not important) spectral features from the facts. These are the Rules. See Table 2 for feature detail. The idea behind the fact-to-rules process is to generalize the spectral features such that they can be found in non-library (and image) spectra.
Table 1: Fact Table for Alunite AL706. N Features: 6, N Elements: 4, Feature Tolerance (depth): 0.0500000, Wavelength Tolerance: 0.0200000, Depth Tolerance: 0.9800000.
Listing of the absorption feature parameters for the extracted features shown in the spectral plot at left in Figure 4. These are the Facts.

<table>
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<th>Position</th>
<th>Depth</th>
<th>FWHM</th>
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<th>Right</th>
<th>Slope</th>
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<tr>
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<td>0.3467</td>
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<td>-0.1257</td>
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</tr>
</tbody>
</table>

Table 2: Rule Table for Alunite AL706. N Features: 6, N Elements: 4, Feature Tolerance (depth): 0.0500000, Wavelength Tolerance: 0.0200000, Depth Tolerance: 0.9800000. Listing of the absorption feature parameters for the extracted features shown in the spectral plot at right in Figure 4. These are the Rules.

<table>
<thead>
<tr>
<th>Feat</th>
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Spectral Variability and Separability Analysis
The fact and rule procedure described above produces self-consistent results for specific sites, but takes spectral variability into account only by the setting of somewhat arbitrary tolerances. Thus, performance is negatively impacted when using the rules developed for one site for identification of materials at another site with different spectral variability. When multiple spectral measurements of specific materials are available, however, we can use automated variability analysis to better define the diagnostic spectral features and acceptable tolerances. Spectral grouping provides the means of calculating spectral variability based on group feature statistics. A group is a collection of similar spectra, or members. Group features are those features that are found to be “in-common” between (shared by) all the group members. The groups can be manually (interactively) defined using a series of similar spectra (Kruse and Lefkoff, 1993). Spectra can also be automatically extracted from regions of interest (ROIs) or from HSI data to
form groups. This provides a simple way of taking into account both spatial and spectral variability.

We have also developed methods for automatically grouping similar spectra, separating spectra that are unique and excluding dissimilar materials (spectral separability). This approach uses a "weighted feature match percent", or score between a given spectrum and every other spectrum in the library. This score is calculated between spectra A and B as 
\[
\frac{\text{(sum of weights for features in common from A) + (sum of weights for features in common from B))}}{\text{(sum of all weights for features in A)+(sum of all weights for features in B)}}
\]
This results in a "weighted feature match percent" matrix, or score matrix. We then average values across rows that are greater than a user-provided threshold (typically 80% match) and do a reverse sort on these values. This removes dependency on the order of the spectra in the spectral library. We next pass through the spectra in the order highest to lowest average score and assign spectra to groups. Assignment to a specific group is done as: for spectrum A, if it's not already in a group, get all spectra that have a weighted feature match percent greater than the threshold and assign them to a new group. This is repeated until all spectra are used. We then create a group file that can be used in spectral variability analysis. This process automatically creates a “unique materials library” and simultaneously a “featureless materials library”. The unique materials is analyzed using the Spectral Expert approach to build rules, while the featureless materials can be passed on to another, better suited analysis algorithm (as featureless materials can not be analyzed using the Spectral Expert approach).

Whether grouped manually, or using the Spectral Separability approach, grouped spectra are individually analyzed to extract features and the positions and characteristics of spectral features are compared to determine multiple “in-common” features (Figure 5). The statistical variability of diagnostic spectral features within each group of spectra with the same features is used to define tolerances for the rules using either the full range or the standard deviation of the parameters. These are then saved as a rule file for use by the expert system.
Figure 5. Spectral Grouping and Variability. Top Left: Spectral plot for 7 muscovite spectra graphically showing variability. Top Right: Continuum-removed plot with in-common feature marked. Vertical arrow marks band center for the group. Horizontal arrow marks the FWHM for the group. The direction of the horizontal arrow indicates the asymmetry (asymmetrical right in this case). The bottom panel shows the group statistics.

Once variability has been analyzed and group rules defined, then characteristic group spectra can be interactively compared if desired to refine rules and improve separability between groups. The refined rules are used to analyze unknown spectra by applying the feature extraction and analysis to the unknown, then comparing the results to the rules.

**Spectral Expert Identification**

Individual unknown reflectance spectra or HSI datasets are matched against the feature-based expert system rules for identification using an empirical probability. “Certainty Probability” as used in the Spectral Expert is an empirical measure of the degree of fit of an unknown spectrum to the rules based on the number of rules satisfied for an unknown spectrum versus the total
number of rules for the reference spectrum (Kruse and Lefkoff, 1993, 1999; Kruse et al., 1993). Weights calculated during the feature extraction process as the ratio of the band depth of a feature to the strongest absorption feature depth in the spectrum are applied to their corresponding rules. A simple equation describes the relationship, which we have implemented as Continuum-Removed, Feature Extraction (CRFE) Score.

CRFE Score (Certainty Probability) = A/B

Where A=Sum of the Weights of Satisfied Rules and B=Sum of the Weights of all of the rules.

For example in a case where there are three absorption features in the rule base for a particular material, with band depth weights of 1.0, 0.48, and 0.30 respectively and only the bands with the 1.0 and 0.30 weights were found in the unknown, the certainty probability can be calculated as

CRFE Score = (1.0 +0.3)/(1.0 + 0.48 + 0.3) = 0.73.

A feature based mixture index (FBMI) can also optionally be calculated to help judge the success of the feature-based analysis approach. FBMI looks at the residual spectral features after matching a given material’s features from the rule base. Higher FBMI scores indicate that more spectral features remain to be analyzed (an indication that either the material of interest is not in the rule base, or that there are additional materials influencing the spectral signature). FBMI is computed as:

FBMI= Sum(A)/B

where: A = Weights of extra features and B = Total number of extra features.

We have also implemented a Root Mean Square (RMS) error method of comparing the known and unknown spectra within the Spectral Expert. This is similar to both the U. S. Geological Survey (USGS) “Tetracorder” algorithm (Clark et al., 2003a) and to “Spectral Feature Fitting”, implemented in the “Environment for Visualizing Images” (ENVI ®) commercial off-the-shelf (COTS) software system (ITTVIS, 2007). The Continuum-Removal RMS (CRRMS) method uses the Spectral Expert rules to determine the number of features and the wavelength ranges to use in the fitting. The continuum is removed for both the known (library) and unknown spectra between the rule-defined continuum endpoints. A multiplicative scale factor (SCALE) is

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determined for each feature and applied to match the absorption band depth of the known to the unknown for each material in the reference library. The Sum of Square Errors (SSE) is calculated between the scaled known spectrum and the unknown spectrum and accumulated with SSE from any prior features for the unknown spectrum. A weighted scale is calculated by multiplying SCALE by the number of samples in the feature and this is accumulated with that from any prior features for the unknown spectrum. An average scale (AVG_SCALE) is computed as the weighted scale divided by the total number of band positions or samples (N_WL) used from all features. The continuum-removed-RMS score (CRRMS Score) is computed as:

\[
\text{RMS} = \sqrt{\frac{\text{SSE}}{\text{N_WL}}} \\
\text{CRRMS Score} = (1 - \text{RMS})
\]

Feature weights can optionally be computed and applied prior to calculation of the CRRMS Score. A feature weight is the total weights of feature/elements in that feature divided by the total of the weights for ALL the features to be used for that spectrum. SSE is weighted by multiplying by the feature weight. The CRRMS Score can also optionally be multiplied by the AVG_SCALE and have a minimum CRRMS score subtracted (MIN_CRRMS) shown as:

\[
\text{CRRMS Score} = (1 - ((\text{RMS} - \text{MIN_CRRMS})>0))\times\text{AVG_SCALE}
\]

The feature-based Spectral Expert and RMS-based Spectral Expert can be combined in a weighted fashion along with other analysis algorithms including the Spectral Angle Mapper (SAM, Kruse et al, 1993b), Binary Encoding (Goetz et al., 1985), and Spectral Feature Fitting (ITTVIS, 2007). In all cases, the result for analysis of a single spectrum is a score between 0.0 and 1.0 for each specific material in the spectral library rules, or for hyperspectral data, a classified image showing the predominate material on a per-pixel basis along with a score image (between 0.0 and 1.0) for each material. When using the feature-based method, the feature-based-mixture-index (FBMI) can also be calculated to determine if there are extra spectral features in addition to those that best fit the defined rules.
Results

The Spectral Expert

The main outcome of our research is a unified “Spectral Expert” software prototype incorporating our approaches, algorithms, and methods and case histories demonstrating application to HSI data. The Spectral Expert is a plug-in to the ENVI hyperspectral analysis software (ITTVIS, 2007), designed to allow non-experts to perform spectral feature analysis utilizing spectral libraries, variability statistics, and the rule-based expert system. The software provides interactive spectral viewing and basic feature analysis capabilities. This includes viewing, automated continuum-removal, feature extraction, and feature characterization for individual spectra. It also includes functionality to allow grouping of similar spectra and automated determination of key (shared) spectral features and variability. The rule building can be performed either automatically or interactively. Finally, the software performs comparison of unknown spectra against the defined rules (expert system) to permit identification of candidate materials based on scoring of matched rules. Spectral Expert identification consists of three related functionalities: 1) The Single Pixel Expert, 2) The Spectral Library Expert, and 3) The HSI Expert.

The Single Pixel Expert applies the previously described continuum removal, feature extraction, and identification methods to single spectra. These can be from an ASCII file, a spectral library, an average of an image region of interest, or a single HSI data spectrum. Basically, any spectrum that can be plotted using the ENVI software can be analyzed. The user selects the predefined rule file to use and the individual spectrum to be identified. The unknown spectrum is compared to the rules and the CRFE Score is calculated. The unknown is ranked against all of the reference spectra in the library, assigning a CRFE score to each. The materials in the library are listed in ranked order; 1.0 is a perfect match and 0.0 is no match. The FBMI is also calculated for each material. Materials having a score of 0.0 used all of the features in the identification, while those with a score of 1.0 used none of the features and were not identified. A table is available showing which rules were matched (Table 3) along with a plot comparing the unknown to the known spectrum (not shown). Other analysis methods (CRRMS, SAM, SFF, and Binary Encoding (BE) can be used for weighted analysis (Figure 6).
Figure 6: Single Pixel Expert results. Single Pixel Expert showing scores for weighted analysis methods. Perfect matches of 1.0 occur for several similar minerals. The best match also has an FBMI score of 0.0 indicating no features left over from the analysis.

Table 3: Feature Table Information showing comparison between Unknown Spectrum (left 4 columns) and best match Rule Spectrum (right 4 columns). Plus sign (+) next to the weight indicates that a rule has been matched. If a rule was not matched, there would be a minus (-) sign next to the weight. If the rule was out of range on the unknown spectrum, there would be an exclamation point (!) next to the weight.
The Spectral Library Expert works on a complete spectral library, treating each member of the spectral library as an unknown spectrum. It removes the continuum, extracts features, and uses the predefined Rule File with all the standard parameters and weighting functions to identify each member of the library. For each spectrum, the highest match (Total Score) becomes the name of that spectrum in the new output spectral library. The output is a new spectral library with Spectral Expert identified names. If there is no match at the selected score threshold (say 75% for example), then the spectrum name will be “No match at threshold 0.75”. If there are multiple matches at the selected score threshold, then the spectrum name will be “Multiple Matches” and the name will include the number of matches, the score, and the top (first) match out of the multiple matches (Figure 7).

Figure 7. Spectral Library Expert results.
The HSI Expert applies the continuum removal to HSI reflectance data on a pixel-by-pixel basis, automatically locates and extracts absorption features, calculates the spectrum parameters, and compares the extracted features to the Spectral Expert Rule File. A “rule image” is constructed for each material in the spectral library with a 0.0 to 1.0 score showing the match to the rule for each specific material. There is one rule band for each material in the rule image. An ENVI classification image is also generated showing the material having the highest score in the rule image (the predominant material). An optional Feature-Based Mixture Index (FBMI) image can be produced in which the darkest pixels represent those areas with the fewest extra spectral features and the brightest areas those with the most unused features. Any of the other weighted options present in the Single Pixel Expert or Spectral Library Expert can also be applied, including the CRRMS analysis (similar to the USGS Tetracorder algorithm). See the case histories below for additional detail and examples.

**Spectral Libraries and Default Rules**

The Spectral Expert also includes a series of spectral libraries and associated rules 1) based on libraries released by the U.S. Geological Survey (Clark et al., 1993, 2003b), 2) of selected Field Spectrometer Measurements, and 3) based on HSI image endmembers. The USGS libraries include selected minerals, vegetation, mixtures, coatings, volatiles, and man-made materials. The field and HSI data libraries provide information for minerals and man-made materials in an urban environment.

**Documentation**

The algorithms, software, and libraries are fully documented using an HTML-based help system. Several HTML tutorials accessed from the software menu provide HSI data, describe use of the software, and illustrate specific analysis results.

**HSI Expert Example – Mineral Mapping (Cuprite, NV)**

We have conducted applications testing and research against spectral libraries of a variety of materials (geology, vegetation, man-made materials) and full HSI datasets (AVIRIS and Hyperion) for a variety of targets and backgrounds to develop case histories showing results using the automated rule development and analysis methods. The Cuprite, Nevada HSI Expert example demonstrates mineral mapping using a laboratory spectral library of selected materials.
The Cuprite, Nevada site has been used extensively for nearly 30 years as a test site for remote sensing instrument validation (Abrams et al., 1977; Kahle and Goetz, 1983; Kruse et al., 1990; Hook et al., 1991; Swayze, 1997, Swayze et al., 1998; Rowan et al., 2003). The site is ideal because it is relatively well known, there is little vegetation, there are a variety of minerals with sharp absorption features, and there are some areas of pure minerals. Materials at the surface consist primarily of volcanic rocks that have been hydrothermally altered (changed by hot water passing through the rocks). Cuprite appears to represent a fossilized hot-springs environment (Swayze, 1997; Swayze et al., 1998). Common hydrothermal alteration minerals present include silica (chalcedony), kaolinite, dickite, alunite, buddingtonite (an ammonium feldspar), muscovite, jarosite, and montmorillonite. Two generalized alteration maps (Figure 8) are provided for comparison with the analyses. The left map (Abrams et al., 1977; Rowan et al., 2003) was produced from a combination of multispectral aircraft data analysis and field study and shows alteration mineral assemblages. Silicified areas on this alteration map consist principally of the minerals quartz with minor calcite, alunite, and kaolinite. Opalized areas contain opal, alunite and kaolinite. The argillized areas contain kaolinite and montmorillonite. The more recent map (1997), a generalization of a USGS Tetracorder mapping result (Swayze, 1997), indicates only the (spectrally) predominant alteration mineral mapped at the surface for each pixel using 1996 HSI (AVIRIS) data. It does not generally account for mineral assemblages or mineral mixing (though there is one mixed class, kaolinite-muscovite).

The Spectral Expert was run against Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data of the Cuprite site acquired 19 June, 1997. First a spectral library of selected minerals (multiple examples of alunite, buddingtonite, calcite, chalcedony, dickite, halloysite, jarosite, montmorillonite, and muscovite) from the U.S. Geological Survey’s splib05 spectral library (Clark et al., 2003b and online at http://pubs.usgs.gov/of/2003/ofr-03-395/ofr-03-395.html) was run through the expert system fact and rule building operators. We could have run a more complete spectral library, however, using only those materials known to occur at the site simplifies and speeds the analysis. The AVIRIS data were calibrated to radiance and corrected to reflectance by the Jet Propulsion Laboratory (JPL), Pasadena, California. These data can be downloaded gratis from their FTP site at http://aviris.jpl.nasa.gov/html/aviris.freedata.html. Only the Short Wave Infrared (SWIR) portion of these data from 2.039 – 2.477 micrometers (45 bands) was analyzed. Two different analysis approaches were applied 1) analysis using the rules and only the absorption band parameters (Continuum-removal, feature-extraction, CRFE) and 2)
analysis using the rules and only the CRRMS feature fitting (Continuum-removal, RMS feature fitting). Both produced similar results (Figure 9). The main difference is that the main alunite mineral identified in each case is slightly different, Alunite GDS83 in the CRFE case versus AL706 in the CRRMS case. In both cases, the mapped mineralogy patterns generally mimic that shown in Figure 8, but the HSI data provide significantly more detail than is available in the generalized maps. The Spectral Expert SWIR classification results for the 1997 Cuprite AVIRIS data display mineralogical information similar to that shown in previous analyses by the USGS (Swayze, 1997; Clark et al., 2003a). The main difference between these and the USGS results is that the rules used for mapping were very quickly and automatically defined for the Spectral Expert mapping, whereas the USGS mapping required extensive interactive rule definition (Clark et al., 2003a).

The Spectral Expert CRFE analysis can also provide information in addition to the primary mineral identification. Figure 10 (top two images and bottom left image) shows a series of images of the CRFE score for selected minerals used in the analysis. These can be used to assess individual mineral patterns and mineral assemblages (by examining and combining specific score images). The Feature-Based-Mixing-Index (FBMI, Figure 10, bottom right image) also shows where extra features remain after matching the CRFE rule base. Bright tones on the FBMI image indicate areas that are potentially mixed or that have features not present in any of the reference spectra. While we have not yet done so, implementation of an iterative approach could lead to additional, secondary mineral maps and an improved understanding of mineral mixing and mineral assemblages.
Figure 8. Left: Alteration map of Abrams et al., 1977, as modified by Rowan et al., 2003. Right: HSI alteration map of Swayze, 1997.

Figure 9. Left: Spectral Expert Mineral Map using absorption band parameters (CRFE). Center: Spectral Expert Mineral Map using CRRMS feature fitting. Right: Mineral endmember key. Endmember are from the USGS Splib05 spectral library (Clark et al., 2003b) and colors match the image colors.
Figure 10: Top Left: Alunite rule CRFE score image, Top Right: Calcite rule CRFE score image, Bottom Left: Muscovite rule CRFE score image, Bottom Right: FBMI image. Brighter pixels represent a better match for the three CRFE score images. Brighter pixels in the FBMI image represent areas where not all of the extracted features were matched using the expert system rules.
It is also possible to apply absorption band weights to the RMS solution. In this approach, weights from the Expert System rule file (derived from absorption band depth) are applied to the RMS fit. Thus, matches to the stronger (usually principal) absorption features are more influential in the mineral mapping decisions. Figure 11 shows the results. Note that the mineral mapping appears more coherent for many minerals, better matching the generalized alteration maps shown in Figure 9.

It is also clear from these previous mapping results that significant generalization is required to produce a meaningful and useful mineral map. Much of the pixilation of the mapping results can be attributed to matching individual mineral spectra from the library without regard to spectral variability. In fact, many of the multiple reference mineral spectra are very similar. Accordingly, we next applied spectral variability and separability analysis to the library spectra to produce a new set of more generalized rules. Spectra were both automatically and manually grouped based on shared absorption features for specific minerals. We went from a total of 33 reference minerals (many of which were repeats of similar minerals with the same mineral name) to a reduced number of 10 unique reference mineral groups. We also calculated both the range and standard deviation for specific shared absorption features. The shared features were deemed to be characteristic and these were used to build new expert system rules and re-run the feature-based (CRFE) HSI Expert. The results are shown in Figure 12. Note that some similar minerals have been grouped together because they are not uniquely separable when spectral variability is taken into consideration. Compare to previous alteration maps and classification images.
Figure 11: Generalized CRRMS Spectral Expert mineral map produced by weighting the spectral features used in the RMS mineral mapping.

Figure 12: Generalized Spectral Expert CRFE mineral map produced through spectral grouping based on spectral variability and separability analyses.

Feature-based analysis systems have typically concentrated on identification of minerals and mineralogical mapping (Yamaguchi and Lyon, 1986; Kruse et al, 1993a; Baugh et al., 1998; Clark et al., 2003a). There have been a few attempts at applying these methods to other disciplines (Clark et al., 1992b; Clark and Swayze, 1995; Kruse and Lefkoff, 1999; Kruse, 2000). The major problem with doing so, however, is that an expert usually has to build a set of rules for the material/targets of interest and this requires a significant time investment. The Spectral Expert attempts to mitigate this situation by automating the rule building process.

The Boulder, Colorado, HSI example was selected as a general analog for HSI analysis of areas with unknown materials and no spectral library. The hyperspectral data themselves are used to build a library and corresponding facts and rules. Spectra extracted from the data for specific materials are identified where possible using published spectra, field spectral measurements, and on-site identification after-the-fact. Boulder is an urban site with a variety of materials both natural and manmade, and significant amounts of both dry and green vegetation. Some materials have sharp absorption features in the VNIR/SWIR, others do not. The approach and selected results described here illustrate that the feature-based methods can be applied to unknown areas by a non-expert with a reasonable expectation of successful materials mapping.

For this analysis, the HSI Spectral Expert was run against AVIRIS data acquired October 11, 2003 for the Boulder, Colorado site. Initially, our approach was to find and extract image spectral endmembers (unique spectra) from the HSI data using model-based atmospheric correction and standardized HSI analysis methods (Kruse et al., 2004). This resulted in an HSI endmember spectral library that could be used to develop expert system facts and rules. We first used the commercially available Atmospheric COrrection Now (ACORN) MODTRAN-based atmospheric correction method to produce high quality surface reflectance from the HSI (AVIRIS) data without ground measurements (AIG, 2001; Kruse, 2004). Field spectra measured for targets occurring in the HSI data were also used to refine the atmospheric correction (Kruse et al., 2004). We then used standardized HSI data analysis approaches developed by the 1st author (Kruse) and associates at Analytical Imaging and Geophysics LLC to find and extract the endmembers (Boardman et al, 1995; Kruse and Lefkoff, 1999; Kruse et al., 2003). These are implemented and documented within the ENVI software system (now an ITT Visual Information Solutions [ITTVIS] product) (ITTVIS, 2007). The key point of this methodology is the reduction
of the HSI data in both the spectral and spatial dimensions to locate, characterize, and identify a few key spectra (endmembers). These can then be used as a spectral library to map and explain the rest of the hyperspectral dataset. These methods derive the key spectra from the hyperspectral data themselves, minimizing the reliance on a priori or outside information.

We analyzed the Visible and Near Infrared (VNIR, 0.4 – 1.2 micrometers, 93 bands) and the SWIR (2.0 – 2.5 micrometers, 46 bands) separately for the Boulder AVIRIS data, extracting two separate HSI endmember spectral libraries (Figures 13 and 14). Spectral Expert facts and rules were developed for each wavelength region by analyzing the spectral endmember libraries, and HSI data analysis was then performed using the rules and only the absorption band parameter approach (Continuum-removal, feature-extraction, CRFE). Figure 13 shows the VNIR results. Principal materials mapped include green vegetation, artificial vegetation (astro-turf), colored tennis court surfaces, Fe-rich roof materials and soils, and a variety of other roof materials (1). Naming of specific materials is based on field reconnaissance and spectral measurements using an Analytical Spectral Devices (ASD) field spectrometer. Only a few of the materials (which are listed in Table 4) for which we extracted endmember spectra are classified using the Spectral Expert because of the requirement that they have recognizable spectral features. Most unclassified pixels on the Spectral Expert classification correspond to either dry vegetation or asphalt (which don’t have absorption features in this wavelength range) or to deep shadows. Some materials with only small occurrences have also been omitted from Figure 13 for clarity. Spectral Expert classified image colors match the spectrum colors in the VNIR endmember plot as well as the descriptions in Table 4.

<table>
<thead>
<tr>
<th>Identification</th>
<th>Spectral Feature(s)</th>
<th>Image Color</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green Vegetation (4 varieties)</td>
<td>Feature associated with 0.5 edge of “green” peak, strong chlorophyll absorption feature near 0.68 micrometers</td>
<td>Olive Green and other medium greens</td>
</tr>
<tr>
<td>Astro Turf</td>
<td>Signature similar to vegetation but strongest feature shifted to 0.63 micrometers, weaker features at 0.73 and 0.78 micrometers</td>
<td>Pure Green</td>
</tr>
<tr>
<td>Tennis Court Surface (Green)</td>
<td>Signature similar to vegetation but strongest feature shifted to 0.62 micrometers and feature</td>
<td>Sea Green (dark green)</td>
</tr>
</tbody>
</table>

Table 4: VNIR Material Identification and Mapping
<table>
<thead>
<tr>
<th>Material Description</th>
<th>Matching Spectral Feature</th>
<th>Color Association</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red tennis court surfaces, also some Fe-rich (hematite) roofs (@CU)</td>
<td>Slope feature near 0.53 micrometers and feature near 0.87 micrometers</td>
<td>Red</td>
</tr>
<tr>
<td>Fe-rich roofs and other similar materials</td>
<td>Slope feature near 0.53 micrometers and feature near 0.90 micrometers</td>
<td>Purple</td>
</tr>
<tr>
<td>Other unknown roofing and some soils</td>
<td>Slope feature falling off below 0.6 micrometers</td>
<td>Cyan</td>
</tr>
<tr>
<td>Other unknown roofing</td>
<td>Peak near 0.60 micrometers bounded by slope feature near 0.49 and micrometers 0.95</td>
<td>Orange</td>
</tr>
</tbody>
</table>

Figure 13: Left: Boulder, Colorado AVIRIS false color infrared (CIR) base image. Center: Image-based VNIR spectral endmembers. Right: Spectral Expert VNIR CRFE Classification Image for a feature match threshold of 0.75 (75%). North is to the top and image base is approximately 2.2 km.
Figure 14 shows the SWIR results. Principal materials mapped include dry vegetation, astro turf, carbonate-rich roof materials (calcite and dolomite), and clay/mica-rich soil and roof materials (Table 5). Note that there is a significant amount of speckle (misclassification), which on examination of the spatial locations appears to be associated with dark (shadowed and other similar) pixels. The Spectral Expert does include a provision for using the continuum reflectance level to winnow out false alarms, but this option has not yet been implemented. Additionally, note that only a few of the materials (which are listed in Table 5) for which we extracted endmember spectra are classified using the Spectral Expert because of the requirement that they have recognizable spectral features. Some materials with only small occurrences have also been omitted for clarity. Spectral Expert classified image colors match the spectrum colors in the SWIR endmember plot as well as the descriptions in Table 5.

Table 5: SWIR Material Identification and Mapping

<table>
<thead>
<tr>
<th>Identification</th>
<th>Spectral Feature(s)</th>
<th>Image Color</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calcite (CaCO$_3$ Limestone) in soils and on roofs</td>
<td>Asymmetrical left 2.34 micrometer feature</td>
<td>Red</td>
</tr>
<tr>
<td>Soils and rooftops with clay/mica materials</td>
<td>Strongest feature near 2.2 micrometers with secondary feature near 2.35 micrometers</td>
<td>Pure Green</td>
</tr>
<tr>
<td>Astro Turf and similar</td>
<td>Sharp asymmetrical right feature near 2.31 micrometers with secondary feature near 2.35 micrometers</td>
<td>Blue</td>
</tr>
<tr>
<td>Dolomite (CaMg(CO$_3$)$_2$) in soils and on roofs</td>
<td>Asymmetrical left 2.32 micrometer feature</td>
<td>Yellow</td>
</tr>
<tr>
<td>Unknown</td>
<td>Asymmetrical right 2.32 micrometer feature</td>
<td>Purple</td>
</tr>
<tr>
<td>Dry Vegetation</td>
<td>Features near 2.1 and 2.27 micrometers</td>
<td>Brown</td>
</tr>
</tbody>
</table>
Discussion and Conclusions:
This project developed and implemented an Expert System for analysis of field, laboratory, and hyperspectral imagery (HSI) data. Our approach consists of interactive and automated methodologies for extracting spectral features, characterizing spectral variability, determining key spectral features for specific materials, and estimating the separability of a variety of materials to build expert system rules. Spectral feature information extracted from unknown field spectra, laboratory spectra, or hyperspectral data is used to identify unknown materials using their spectral properties.

The main outcome of our research is approaches, algorithms, and methods implemented in a unified software prototype, the “Spectral Expert” developed within the framework of the
ENVI software and the associated IDL programming language. The software is designed to allow non-experts to perform spectral feature analysis utilizing spectral libraries, variability statistics, and a rule-based expert system. It plugs seamlessly and automatically into ENVI/IDL and provides spectral viewing and analysis capabilities beyond base ENVI functionality, thus leading to an improved understanding of reflectance spectra and hyperspectral data. The software performs comparison of unknown spectra against the defined rules (the knowledge base) to permit identification of candidate materials based on scoring of matched rules.

We have tested the Spectral Expert on full HSI data cubes for several sites and developed case histories illustrating use and results. The Cuprite, Nevada site provides an example of the simplest case – application to minerals with a laboratory spectral library and well-defined spectral features. Results demonstrate basic success, however, even in this simple case, high spectral variability and spectral mixing complicate the analysis. Spectral Expert variability and separability analysis tools help to deal with these issues. The second case, Boulder, Colorado, shows application of the Spectral Expert to characterization of an urban environment where no previous spectral library exists. The results mimic patterns seen in other analyses of the data and ASD field spectral measurements confirm that the feature-based approach is mapping key materials. It is hard, however, to judge the full success of the method, as adequate ground truth does not exist and is difficult to acquire.

The Spectral Expert works best when unique endmembers with well-formed spectral features are used. Its preferred application would be for analysis of unique, high-quality reflectance spectra from spectral libraries or culled from the HSI data. Confusion may occur between multiple endmembers with similar spectral features. These endmembers should be combined (as determined by spectral variability and separability analysis) for best results. The feature-based approach is also poorly suited to analysis of spectral mixtures. While the FBMI can be used to identify potential mixtures, the Spectral Expert currently maps only the best matches to specific endmembers. Finally, feature-based methods can not map certain endmembers used in other mapping methods because certain materials do not have spectral features. All of these factors point towards approaches using the feature-based methods in combination with other algorithms. The Spectral Expert presents an alternative and supplement to other statistically-based HSI analysis methods for analysis of full HSI data cubes. It can provide the link between named, known spectral signatures and HSI data.
References:


