Analysis of Spectral Data of Manmade Materials, Military Targets, and Background Using an Expert System Based Approach

F. A. Kruse and A. B. Lefkoff
Analytical Imaging and Geophysics
Boulder, CO 80303 kruse@aigllc.com

ABSTRACT

An expert system developed for use with geologic materials (minerals) has been modified to more generally analyze spectra of all types of materials, including manmade materials, military targets, and background. The methodology requires reflectance spectra, but can also be extended to emissive measurements in the mid-wave infrared (MWIR) and long-wave infrared (LWIR). The spectra of known materials are used as a reference library, which is then analyzed using a continuum-removal/feature-extraction methodology. If multiple measurements of a selected material are present in the library, then these are used to calculate spectral variability and create default tolerances for expert-system rules. The rules are applied against unknown field, laboratory, or hyperspectral signatures in a weighted fashion to identify materials. Implemented as an extension to the "ENVI" remote sensing software system, this approach provides even untrained personnel with the ability to use characteristic spectral properties for analysis of hyperspectral data and spectra from a variety of other sources.

Key words: Expert system for spectral analysis, feature-based spectral analysis, spectral signatures, spectral libraries, hyperspectral data, ENVI Extension.

1. INTRODUCTION

Hyperspectral data have high potential to quickly characterize the Earth's surface for both civilian and military purposes. One of the most difficult hurdles in use of these data, however, is the lack of robust, automated analysis tools that can be effectively utilized by a non-expert analyst. Routine extraction of diagnostic spectral signatures from hyperspectral data is now possible. Once extracted, however, actual identification of the materials utilizing these spectral signatures is still one of the most difficult obstacles.

This research summarizes efforts to automate analysis of spectral signatures from field and laboratory spectrometers, and hyperspectral sensors. Methods developed for the analysis of geologic materials have been modified and enhanced to allow automated spectral identification of endmember spectra using weighted expert system results, binary encoding, the Spectral Angle Mapper (SAM), and Spectral Feature Fitting (SFF)™ in a hybrid identification tool. Spectral Variability Analysis Tools have also been developed to help deal with natural variability within specific target classes. All of these capabilities have been implemented as prototype Plug-In software operating under the ENVI® (Environment for Visualizing Images) software system.

2. FEATURE-BASED SPECTRAL ANALYSIS

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

Two robust feature-based methods have emerged that should be considered as baseline algorithms for identification of materials using spectral features: 1.) An expert-system-based method utilizing absorption band parameters (Kruse, 1990, 1992, 1995, 1996, 1998; Kruse and Lefkoff, 1992, 1993; Kruse et al., 1988, 1990, 1993a), and 2.) the "Tetracorder" method developed by the USGS, Denver (Clark et al., 1987, 1991; 1992a, 1992b, 1999; Clark and Swayze, 1995).

The following describes the expert system approach (method #1 above) previously developed by the authors to allow automated identification of Earth surface materials based on their spectral characteristics in imaging spectrometer data (Kruse, 1990; Kruse and Lefkoff, 1993.

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

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

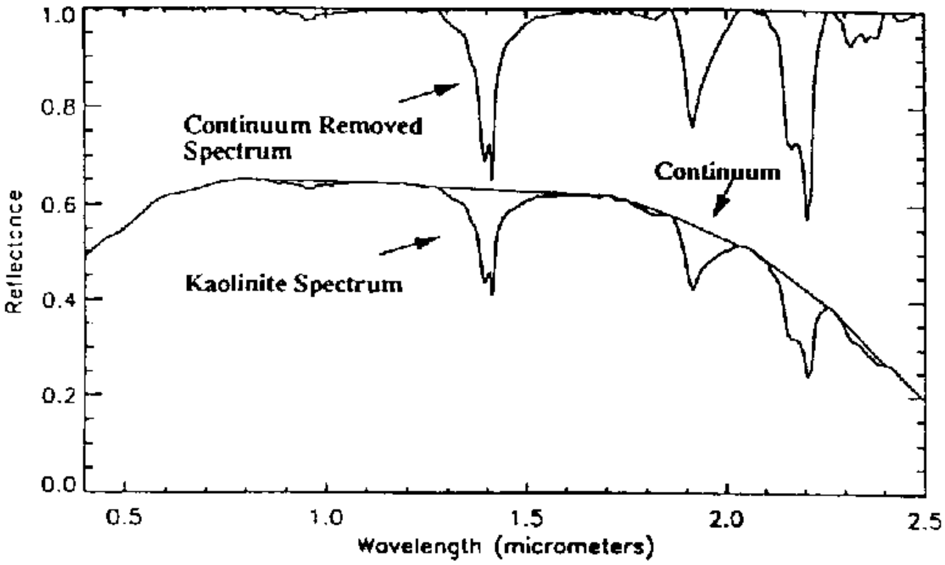


Figure 1. Reflectance spectrum with the continuum and the continuum-removed spectrum.

2).The continuum is divided into the original spectrum to normalize the absorption bands to a common reference (Figure 1). (See Clark and Roush, 1984 for a discussion of division versus subtraction of the continuum).

3). The minima of the continuum-removed spectrum are determined and the 10 strongest absorption features extracted (Figure 1).

4). The wavelength position, depth, full width at half the maximum depth (FWHM), and asymmetry for each of these 10 features are determined and tabulated (Figure 2).

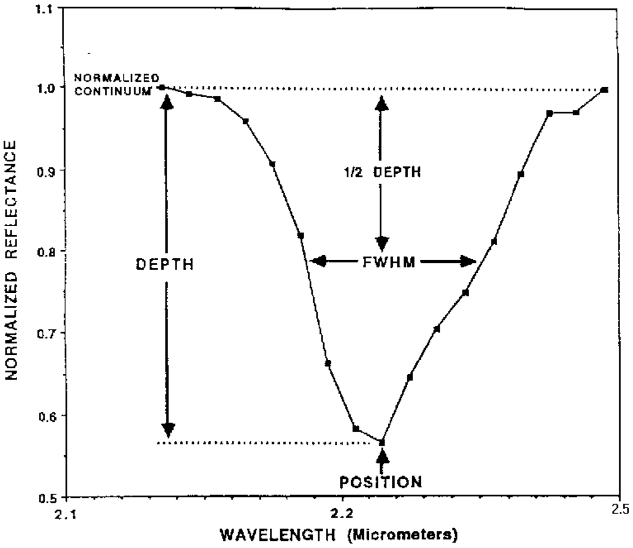


Figure 2. The absorption band parameters position, depth and FWHM.

The asymmetry is defined as the sum of the reflectance values for feature channels to the right of the minimum divided by the sum of the reflectance values for feature channels to the left of the minimum (Figure 3).

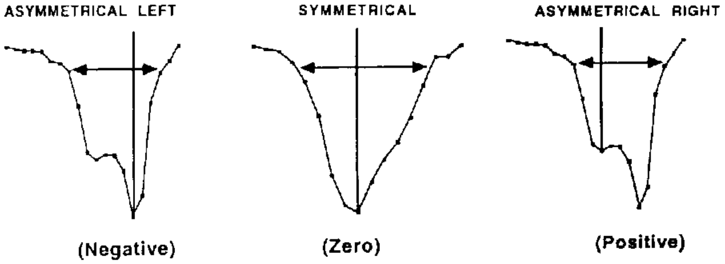


Figure 3. The absorption band parameter asymmetry.

The base ten logarithm is taken of this value to maintain linearity. Symmetrical bands thus have an asymmetry value of zero (the area to the left and right of the band center are equal). Bands that are asymmetrical towards shorter wavelengths have negative asymmetry, while bands 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 is then interactively reviewed simultaneously in both tabular and graphical format to determine if features extracted from the digital spectra are representative of the material measured or are due to impurities. The four parameters derived using the feature extraction procedure are used in conjunction with published spectral information to determine the critical absorption bands and absorption band characteristics for identification of specific materials. Facts and rules are written for each material or group of materials in the database based on the analysis of the spectral library.

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

The expert system described above has been used to analyze AVIRIS data to automatically identify minerals and to map their spatial distributions (Kruse, 1990; Kruse et al., 1993; Lefkoff and Kruse, 1993). The absorption feature positions and shapes of each reflectance spectrum for each pixel were characterized using the automated techniques described previously for individual laboratory spectra. The final products of the expert system analysis were a "continuum-removed" cube with 224 bands containing all of the continuum-removed spectra calculated from the reflectance data, a "feature" cube containing the wavelength positions, depths, FWHMs, and asymmetries for each pixel for the ten strongest absorption features, and an "information cube" showing the location and probability of occurrence of 25 minerals and both dry and green vegetation based on the weighted combination of binary encoding, and feature analysis in the expert system (Figure 4).

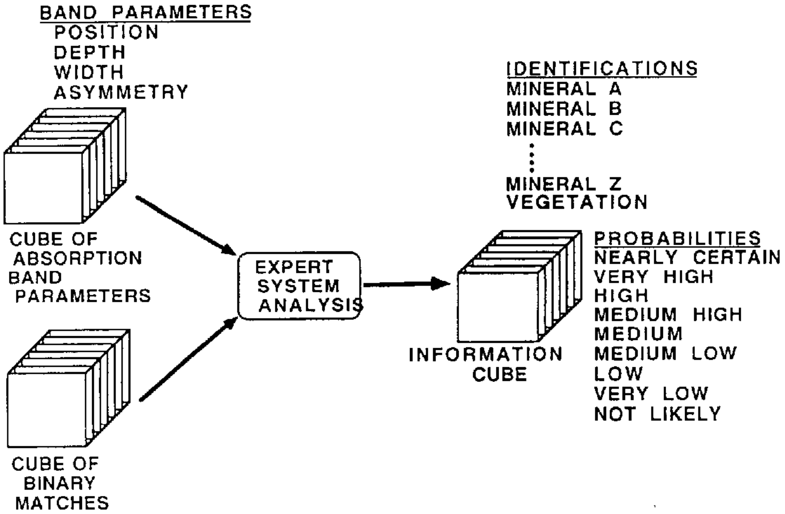


Figure 4. The expert system concept for hyperspectral data analysis.

The information 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%.

3. EXTENSION TO MAN-MADE MATERIALS AND IMPLEMENTATION AS ENVI PLUG-IN PROTOTYPES

While this expert system for analysis of imaging spectrometer data was designed primarily for geologic sites, recent work has shown that it can be applied to other disciplines, provided that sufficient spectral libraries are available for fact and rule definition. For example, 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).

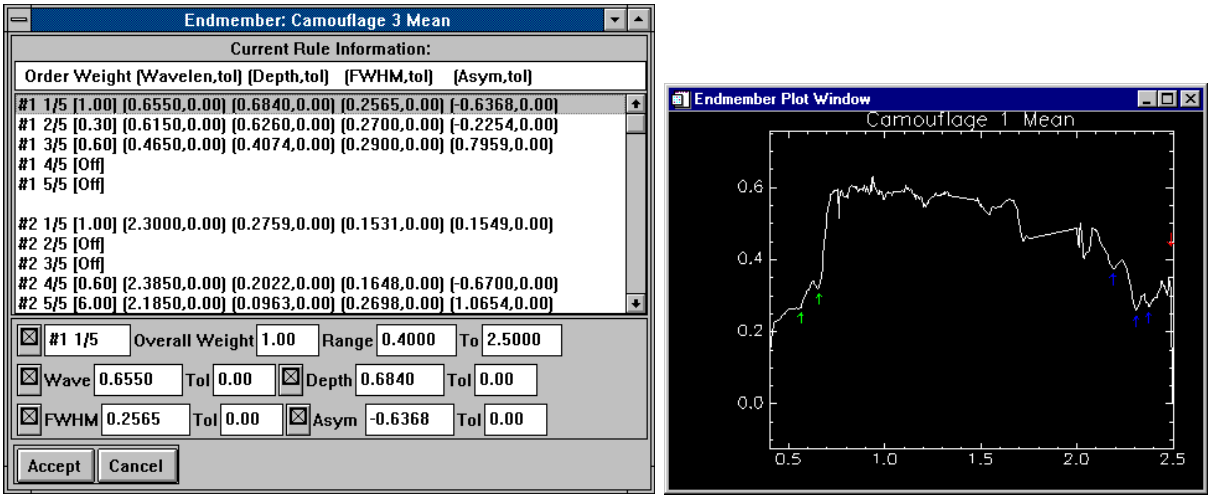
The research described here is built on the expert system concepts described above, but consists of a more generalized implementation (to work on all kinds of materials), and refinements to specifically work on man-made materials. Particular emphasis was placed on spectral libraries containing man-made materials and military targets. Spectral libraries of these materials were provided by the U. S. Army Topographic Engineering Center (TEC). Spectral variability was considered in these analyses and several tools were developed for building expert systems rules and analyzing field, laboratory, and hyperspectral (HYDICE) spectra. Implementations have been prototyped for both single spectrum identification, and image mapping based on identification of the principal materials in each pixel of a hyperspectral dataset, however, to-date, only the single-pixel version has been completed.

The Environment for Visualizing Images (ENVI) was used as the development environment for prototype software to perform expert system analysis of spectral data as described above. ENVI provides a library of procedures and programming tools (user functions) written in IDL® (Interactive Data Language) to handle input, output, plotting, reports, and file management. A set of ENVI compound widgets are provided to simplify writing graphical user interfaces (GUI) and give ENVI Plug-In routines the same look and feel as ENVI. The processing routine takes the input image or spectral data, processes the data, and outputs a new image, plot, report or other result. The procedures followed in implementing an ENVI Plug-In function are:

1. Creating the algorithm itself
2. Interactive prototyping using IDL
3. Wrapping the algorithm utilizing ENVI User Functions and compound widgets
4. Embedding the new ENVI menu item (ENVI 3.2)
5. Placing the ENVI Extension for automated loading
6. Testing and Documentation

Several prototype capabilities developed as part of this research were implemented within ENVI, including routines to remove the continuum and extract spectral features, build “facts”, interactively build and edit “rules”, and identify spectra. The generalized knowledge base

(Facts) for materials are extracted from a spectral library. Parameters derived using the feature extraction procedure are used in conjunction with spectral variability analysis (see below) to determine the critical absorption bands and absorption band characteristics (Rules) for identification of specific materials. Facts and rules are derived for each material or group of materials in the database based on the analysis of the spectral library (Figure 5).

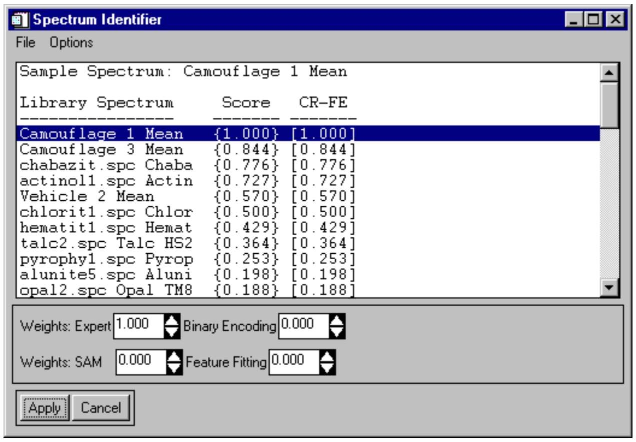


```
Order Weight (Wavelen,tol) (Depth,tol)   (FWHM,tol)    (Asym,tol)
#1 1/5 [1.00] (0.6550,0.00) (0.6840,0.00) (0.2565,0.00) (-0.6368,0.00)
#1 2/5 [0.30] (0.6150,0.00) (0.6260,0.00) (0.2700,0.00) (-0.2254,0.00)
#1 3/5 [0.60] (0.4650,0.00) (0.4074,0.00) (0.2900,0.00) (0.7959,0.00)
#1 4/5 [Off]
#1 5/5 [Off]

#2 1/5 [1.00] (2.3000,0.00) (0.2759,0.00) (0.1531,0.00) (0.1549,0.00)
#2 2/5 [Off]
#2 3/5 [Off]
#2 4/5 [0.60] (2.3850,0.00) (0.2022,0.00) (0.1648,0.00) (-0.6700,0.00)
#2 5/5 [6.00] (2.1850,0.00) (0.0963,0.00) (0.2698,0.00) (1.0654,0.00)
```

☒ #1 1/5 Overall Weight 1.00 Range 0.4000 To 2.5000
☒ Wave 0.6550 Tol 0.00 ☒ Depth 0.6840 Tol 0.00
☒ FWHM 0.2565 Tol 0.00 ☒ Asym -0.6368 Tol 0.00

Figure 5: Edit Spectrum Rules with Plot

For identification, the facts and rules derived from the spectral library are used to analyze each unknown spectrum (field, laboratory, or hyperspectral pixel). Spectra are assigned a score that ranks their match to the rules based on comparison of the feature rules satisfied versus the expected absorption features. The score ranges between 0 and 1.0, with a higher score indicating a better match to the rules derived from the reference spectral library. Procedures such as binary encoding (Mazer et al, 1988), the Spectral Angle Mapper (SAM) (Kruse et al., 1993b; Boardman, unpublished data), or Spectral Feature Fitting can be used with the feature-based approach in a weighted fashion under high noise conditions or where significant features are not present in the materials of interest (common with some military targets). Figure 6 shows an example of the ENVI Plug-In for spectral identification.

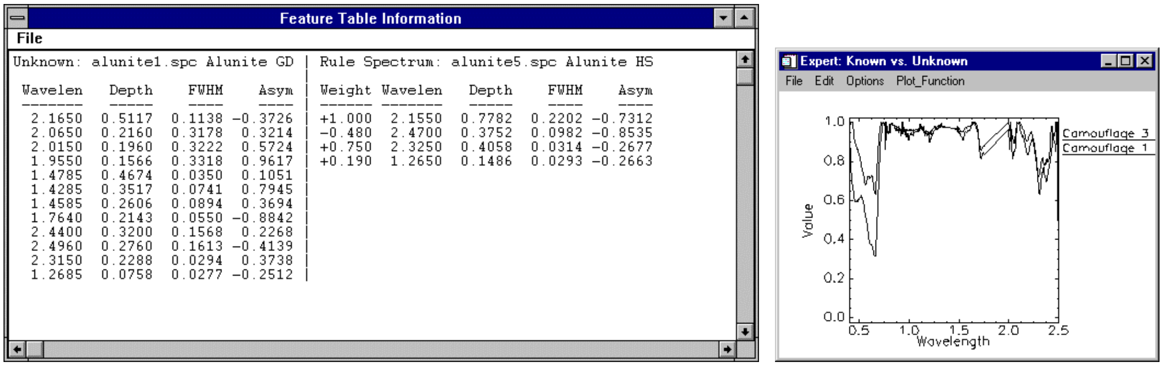


```
Sample Spectrum: Camouflage 1 Mean

Library Spectrum      Score   CR-FE
----------------     ------- -------
Camouflage 1 Mean    {1.000} [1.000]
Camouflage 3 Mean    {0.844} [0.844]
chabazit.spc Chaba   {0.776} [0.776]
actinol1.spc Actin   {0.727} [0.727]
Vehicle 2 Mean       {0.570} [0.570]
chlorit1.spc Chlor   {0.500} [0.500]
hematit1.spc Hemat   {0.429} [0.429]
talc2.spc Talc HS2   {0.364} [0.364]
pyrophy1.spc Pyrop   {0.253} [0.253]
alunite5.spc Aluni   {0.198} [0.198]
opal2.spc Opal TM8   {0.188} [0.188]
```

Weights: Expert 1.000 Binary Encoding 0.000
Weights: SAM 0.000 Feature Fitting 0.000

Figure 6: The TEC Spectrum Identifier ENVI Plug-In Higher scores indicate better match to the rules.

Also, because this is a rule based system, the spectrum identification can be fully justified in terms of the rules satisfied to help interactively verify the identifications.



```
Unknown: alunite1.spc Alunite GD | Rule Spectrum: alunite5.spc Alunite HS
                                 |
 Wavelen   Depth    FWHM    Asym | Weight Wavelen   Depth    FWHM    Asym
 -------  ------    ----    ---- | ------ -------  ------    ----    ----
  2.1650  0.5117  0.1138 -0.3726 | +1.000  2.1550  0.7782  0.2202 -0.7312
  2.0650  0.2160  0.3178  0.3214 | -0.480  2.4700  0.3752  0.0982 -0.8535
  2.0150  0.1960  0.3222  0.5724 | +0.750  2.3250  0.4058  0.0314 -0.2677
  1.9550  0.1566  0.3318  0.9617 | +0.190  1.2650  0.1486  0.0293 -0.2663
  1.4785  0.4674  0.0350  0.1051 |
  1.4285  0.3517  0.0741  0.7945 |
  1.4585  0.2606  0.0894  0.3694 |
  1.7640  0.2143  0.0550 -0.8842 |
  2.4400  0.3200  0.1568  0.2268 |
  2.4960  0.2760  0.1613 -0.4139 |
  2.3150  0.2288  0.0294  0.3738 |
  1.2685  0.0758  0.0277 -0.2512 |
```

Figure 7. Justification of spectral match. A "+" sign in the first column of the right side of the list indicates a match. A "-" sign indicates that that specific rule was not matched. The plot to the right allows visual comparison of the known versus the unknown continuum-removed spectrum.

The ENVI Plug-In functions developed as part of this research have been tested on field and laboratory spectra, and individual spectra and Regions of Interest from HYDICE data. Results indicate that the single pixel expert system approach is effective on some classes of manmade materials as measured with HYDICE data. These include camouflage materials and selected paints as well as vegetation. It is less effective on other classes of material (principally featureless materials such as asphalt, concrete, etc. The use of additional weighted parameters (Spectral Angle Mapper, Binary Encoding, and Spectral Feature Fitting) helps to deal with some of these other materials that do not have strong spectral features. A modified version of the spectral identification plug-in has been implemented in the ENVI core as the ENVI Spectral Analyst™.

The Spectral Feature Fitting (SFF)™ algorithm implemented as part of this research in the Spectrum Identifier is a derivation of approach #2 mentioned in Section 2 above (Clark et al., 1990, 1991). SFF works across a spectral range selected by the user. A continuum is removed from each spectrum in a reference spectral library over the selected spectral range (Kruse and Lefkoff, 1993). The continuum is then removed from the unknown spectrum and the band depth of the reference spectrum and the unknown spectrum are compared. The continuum-removed spectrum is subtracted from 1.0 and then a scaling factor is used to scale the depth of the reference spectrum to match the unknown spectrum. A larger scaling factor then represents a deeper spectral feature. Finally, a least-squares-fit is used to determine the root-mean-square (RMS) error between the reference and the unknown spectrum. A lower RMS score represents a better match of the unknown to the reference. A more robust implementation of this algorithm, which utilizes specific absorption features, is currently only available at the U.S. Geological Survey, Denver, as "Tetracorder" (Clark et al., 1999).

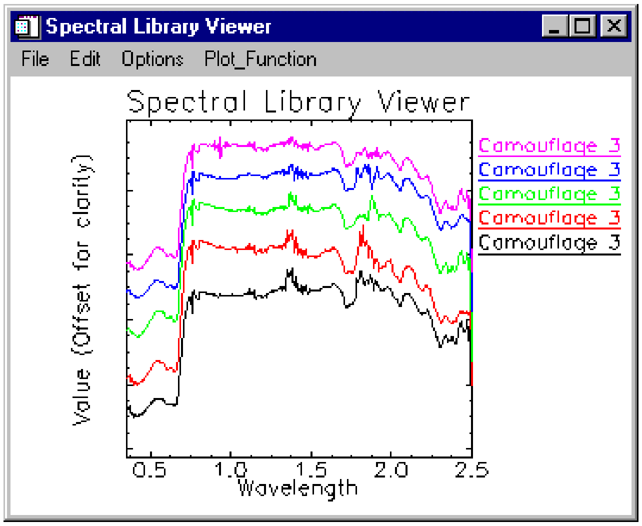
4. SPECTRAL VARIABILITY

Accumulation of expert knowledge is one major problem to any expert system approach. Most efforts to build knowledge based spectral analysis systems rely on tedious, manual extraction of key parameters from library spectra to build the rules required for analysis. This research used library spectra and statistical analysis to assist with automatic development of rules and rule tolerances based on spectral. The goal was to improve knowledge-based spectral identification procedures by automating as much as possible the rule definition procedure. The approach was to utilize spectral libraries with multiple measurements of manmade materials, soils, and vegetation as well as existing mineral libraries (for background materials) to conduct statistical analyses directed at automatically producing rules for identification. A prototype ENVI Plug-In designed and implemented as part of this work included tools for statistically matching and tabulating features contained in multiple measurements of the same material. These include methods for:

- Selecting spectra and grouping
- Matching spectral features within a group within a designated tolerance
- Calculating the statistics for matched absorption features
- Building default tolerances for position, depth, FWHM, and asymmetry based on the statistics
- Producing a "standard" rule file for use with the Spectrum Identification Plug-In.

The following shows an example of rule/tolerance building using multiple spectra (five spectra measured for camouflage with similar spectral features, but some natural variability).

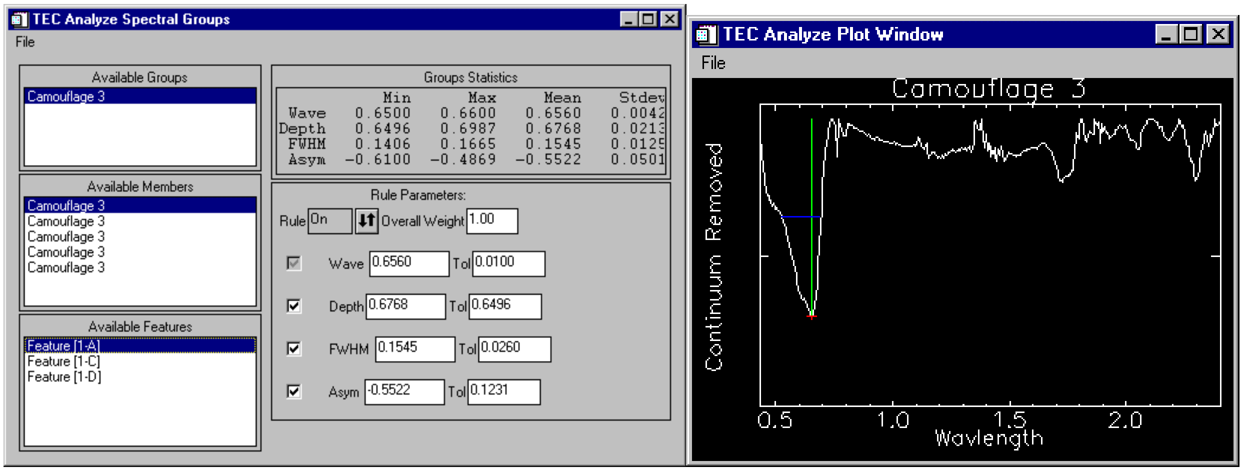
The continuum is removed from the five spectra and individual features are compared to determine if there are common features between the spectra (Figure 8). If a feature doesn't occur in all of the candidates (within the specified tolerances), then no statistics are calculated, and that feature is not included as a critical feature for identifying the group. If a feature occurs in all of the spectra in the selected group, then that feature is defined as critical, and statistics are calculated to determine tolerances for the rules (Figure 9).



```
Tabulated Data from Camo3.rul

1. Camouflage 3<~0.3500, 2.5000
;Wt   Wave   Dept   FWHM   Asym
;--   ---    --     --     ---
 0.70 0.6500 0.7043 0.3027 -0.6943
 0.67 0.6100 0.6657 0.3059 -0.3355
 0.56 0.4450 0.5593 0.3189  0.6407
 0.30 2.2950 0.2971 0.1568 -0.0251
 0.22 1.7250 0.2178 0.1072 -0.5334

2. Camouflage 3<~0.3500, 2.5000
;Wt   Wave   Depth  FWHM   Asym
;--   ---    --     --     --
 0.71 0.6500 0.7130 0.3023 -0.6855
 0.66 0.6100 0.6644 0.3050 -0.3282
 0.55 0.4250 0.5469 0.3214  0.8339
 0.28 2.3100 0.2797 0.1549 -0.3536
 0.26 1.7200 0.2569 0.1375 -0.3941

3. Camouflage 3<~0.3500, 2.5000
;Wt   Wave   Depth  FWHM   Asym
 0.67 0.6600 0.6695 0.3005 -0.8100
 0.61 0.6150 0.6113 0.3066 -0.3544
 0.53 0.4250 0.5270 0.3145  0.8509
 0.29 2.2950 0.2946 0.1515 -0.0482
 0.20 1.7200 0.2032 0.1743 -0.1595

4. Camouflage 3<~0.3500, 2.5000
;Wt   Wave   Depth  FWHM   Asym
 0.72 0.6600 0.7181 0.3051 -0.7812
 0.68 0.6150 0.6781 0.3110 -0.3502
 0.56 0.4550 0.5641 0.3210  0.5740
 0.24 2.3050 0.2415 0.1443  0.0433
 0.17 1.7200 0.1685 0.0890 -0.2541

5. Camouflage 3<~0.3500, 2.5000
;Wt   Wave   Depth  FWHM   Asym
 0.68 0.6500 0.6818 0.2997 -0.6804
 0.63 0.6100 0.6304 0.3025 -0.3167
 0.51 0.4250 0.5142 0.3117  0.849
 0.31 2.3000 0.3068 0.1564  0.157
 0.15 1.7200 0.1469 0.0832  0.5040
```

Figure 8. Plot of 5 stacked spectra for the material "Camouflage 3" from the spectral library. The text below shows the features and feature parameters extracted by analysis of the spectra using continuum removal and feature extraction.

Once the statistics have been compiled, then they can be analyzed using the "Analyze Spectral Groups" ENVI Plug-In. Only those absorption features designated as "critical" because they occurred in all of the spectra are available for analysis.



Groups Statistics

	Min	Max	Mean	Stdev
Wave	0.6500	0.6600	0.6560	0.0042
Depth	0.6496	0.6987	0.6768	0.0213
FWHM	0.1406	0.1665	0.1545	0.0125
Asym	-0.6100	-0.4869	-0.5522	0.0501

Rule Parameters:

Rule On Overall Weight 1.00

☑ Wave 0.6560 Tol 0.0100

☑ Depth 0.6768 Tol 0.6496

☑ FWHM 0.1545 Tol 0.0260

☑ Asym -0.5522 Tol 0.1231

Figure 9. Tabulated Rule Data for the 5 Camouflage 3 spectra used in the analysis and a plot of one of the critical bands showing the location and FWHM.

At this stage, individual rules can be interactively turned on or off and the tolerances can be edited if desired. When satisfied with the rules, they are saved to a standard rule file, after which they can be further modified rule editing and then used in the Spectrum Identifier Plug-In.

5. CONCLUSIONS

This research demonstrates that spectral analysis tools first designed for identifying geologic materials are extensible to quickly characterize the Earth's surface for both civilian and military purposes. AIG's research pulls together efforts in the areas of expert system analysis of reflectance spectra to produce tools that bring complex analysis capabilities to the average user. The implementation of these tools in a portable image processing system (ENVI) results in an automated analysis methodology applicable to both civilian and military use of hyperspectral data. These reusable tool sets will be available for integration into operational hyperspectral analysis using ENVI.

6. ACKNOWLEDGMENTS

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