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Considerations in collecting, processing, and analysing high spatial resolution hyperspectral data for environmental investigations

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Abstract. This paper briefly describes the methods available for collection, atmospheric and geometric correction, and processing of hyperspectral imagery. Discussion of data capture concentrates on logistics of integrating image acquisition with field data collection. Atmospheric correction is required to use the imagery with reference spectra from field and laboratory sensors; a variety of methods for atmospheric correction are described. Geometric correction is required for integration of the image data and derived products with other geographic information. A description of methods for single and multiple feature identification is provided. These all focus on the analysis of the spectral description of surface materials provided by hyperspectral imagery; methods for multiple feature identification take advantage of high spectral dimensionality of the imagery to identify sub-pixel components. A role for spatial analysis combined with spectral analysis in interpretation of environmental features is identified.

Key words: High spatial resolution, hyperspectral imagery, analysis, atmospheric and geometric correction

JEL classification: C63, C69, C89

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1 Introduction

The development of widely accessible high spatial resolution hyperspectral (HSRH) data is relatively recent, and thus is a relatively novel data source for analysis of large spatial scale environmental and earth science questions. Although the principles of spectroscopy are well known and methods for analysis are well developed, particularly for spectra collected in laboratory environments (e.g.,Clark et al. 1992; Clark and Swayze 1995), the heterogeneity of landscapes and earth surface features in large scale environmental studies presents new challenges and opportunities for analysis of hyperspectral imagery. Likewise, although principles of ground truthing and accuracy assessment are well established in remote sensing literature (e.g., Congalton and Green, 1999), the high spatial resolution of modern data presents challenges to field data collection and data analysis.

This paper describes some of the major technical issues in capturing and processing high spatial resolution hyperspectral imagery. We also guide the reader to major literature on these topics, much of which is contained in the "grey literature" of conference proceedings and web sites. Methods and analyses applied to high spatial resolution hyperspectral imagery are described in the same sequence that a typical user encounters. Explanation of data collection and image pre-processing is followed by description of a series of methods for data analysis. We conclude with suggestions for ways to enhance future analysis of hsrh data.

2 The nature of high spatial resolution hyperspectral imagery

The principles of spectroscopy employed in hyperspectral image data collection and processing are well known and have been used for many years (Goetz et al. 1985). Spectroscopy measures the electromagnetic radiation from objects as a spectrum, with different materials having different characteristic spectra based on their chemical composition. For example, minerals (Goetz et al. 1985; Kruse et al. 1993; Clark and Swayze 1995), vegetation (Ustin et al. 1999), plant properties (Gamon et al. 1993, 1995; Roberts et al., 1993; Ustin et al. 1996) snow and ice (Clark and Swayze 1995), and soils (Palacios-Oreuta and Ustin 1996) have all been successfully and directly identified and measured using spectroscopy. Hyperspectral remote sensing measures the spectral properties of the environment using imaging spectrometers placed on airborne and spaceborne platforms. A list of hyperspectral imaging systems can be found at http://rst.gsfc.nasa.gov/sect13/is_list.html.

The word "hyper," literally translated, means "excessive in extent or quality" or "over, above, beyond" (Gove 1976, p. 1112). In contrast to multispectral scanners, the amount of spectral information recorded by hyperspectral spectrometers thus exceeds the amount required to identify many features. This "excess" information results from the high spectral resolution (i.e., narrow band widths) relative to multispectral scanners and the wide range of spectra that are recorded, which together enable users to extract subtle differences in spectral signatures. There is no absolute definition of how many bands are needed or how narrow the bandwidths need to be to make imagery "hyper," although most sensors that are called hyperspectral have 48 or more bands with spectral resolutions of 20 nm or smaller. A number of the key characteristics that influence the data collected by hyperspectral sensors are described in Table 1.

Just as there is not a specific number of bands required for imagery to be hyperspectral, there is no clear threshold of pixel size at which coarse spatial resolution imagery transitions to high spatial resolution imagery. For the purposes of our work, we define high spatial resolution as imagery with pixels that are 5 m or less in size. This size range represents (for hyperspectral imagery), a spatial resolution that has only recently become available as sensors have been mounted on low flying aircraft. In addition, pixels that are 5 m or smaller in size present georectification, coregistration and ground truthing problems that are not present with coarser spatial resolution hyperspectral analysis.

3 Data collection and pre-processing of the imagery

3.1 Flight planning for high spatial resolution hyperspectral data collection

At the present time, acquisition of airborne hsrh imagery is limited by instrument availability and cost. A number of instruments, such as Probe1 and HyMap, are commercially available, while other instruments such as AVIRIS are available to NASA-supported researchers. In addition to financial costs, data collection using commercial instruments has a number of logistical constraints. Weather conditions influence flights and the quality

Table 1. Properties of imaging spectrometers

Property	Description
Spectral range	describes the measured range of the electromagnetic spectrum. Different materials absorb in different wavebands thus the spectrum recorded by an instrument should include these characteristic wavebands to help identify different materials. Airborne and spaceborne instruments typically record in the visible and near infrared spectrum (0.4 μm to 2.5–3.0 μm).
Spectral bandwidth	the width of an individual band in the spectrometer. Bands are adjacent in a spectrometer to provide continuous measurement of the entire spectrum. The narrower the bandwidth, the narrower the absorption features that can be measured and the greater the resolution of the spectrum.
Bandpass profile	describes the shape of the response of the detector in the spectrometer across the spectral bandwidth. The shape is usually gaussian. The width of the bandpass profile is described as the wavelength at the 50% response level of the function, the Full Width at Half Maximum.
Spectral sampling	the distance in wavelength between bandpass profiles for each channel as a function of wavelength.
Signal to noise ratio	describes the precision with which the spectrometer measures the spectrum relative to the detail needed to resolve particular features. A lower signal to noise ratio is needed for strong spectral features while a higher signal to noise ratio is needed for weak features.

of data collected, flight scheduling must be coordinated with field data collection, since ground-based data may be required on the day of the flight or in the several days immediately surrounding it. We suggest that individuals planning HSRH-flights have a project management strategy that particularly focuses on the logistics of data collection.

3.2 Initial considerations for image processing and field data collection

As with any remote sensing analysis, the nature of field data collection and image pre-processing required to use hsrh imagery will depend on how the data will be analysed. Of particular importance is whether a "top-down" or "bottom-up" analysis is envisioned.

Top-down approaches use field mapping to train the imagery to detect certain features. Field surveys and accurate georeferencing and co-registration of images and field maps are required for top-down approaches. In some instances however, atmospheric corrections may not be required with top down approaches. The small geographic extent of hsrh images reduces the potential for significant variations in atmospheric effects across the scene, while mapping field features directly to the image means that the classifying algorithm can incorporate atmospheric effects into the feature spectra as it searches the image to find similar features. A particular feature type will therefore probably appear similar across the entire image and the atmospheric effects should not overly confuse the mapping process. As one extends the analysis over larger areas or between images, however, ignoring atmospheric effects becomes increasingly untenable.

In contrast, bottom-up approaches typically use ground-based or laboratory-based spectral libraries to identify key features. In this situation, atmospheric corrections are absolutely essential, because the effects of the atmosphere must be removed in order for image spectra to match library spectra. Because the identification of features relies on the matching of spectra rather than overlaying ground maps on the imagery, georeferencing and image co-registration can be relatively unimportant in the bottom-up approach. In bottom-up approaches using library spectra accurate atmospheric corrections are particularly important, where specific bands are very strongly affected by atmospheric composition (Table 2). The great advantage of bottom-up approaches is that the same spectral library can be extended over wide areas and across multiple images to identify specific feature types, as long as the images are atmospherically corrected.

Table 2. Absorption wavelengths of common atmospheric constituents

Constituent	Absorption wavelength (μm)
Ozone	0.35
	9.6
CO_2	1.6
	2.005
	2.055
Water	0.69
	0.72
	0.76

HSRH-imagery can sometimes provide the unique opportunity to take advantage of the strong points of both top-down and bottom-up approaches, while avoiding some of their pitfalls. Because the pixel resolution is small, the image may contain pixels that contain only the feature of interest (e.g., a wetland, a plant species type, or a particular soil type). Spectra can be collected from these pixels to create an airborne spectral library. The great advantage of this type of library is that it incorporates the atmospheric effects in the feature spectra and therefore does not require applying the many assumptions and uncertainties inherent in atmospheric corrections and the matching of image spectra with library spectra. Likewise, the ability to visually identify and map these pure pixels directly to the image (much like an air photo) means that precision field mapping and image georectification may not be necessary to accurately map features on the image.

3.3 Atmospheric corrections

Analytical approaches: As noted above, the data collected by airborne or spaceborne hyperspectral sensors are not immediately comparable to laboratory or ground-based spectra, because the atmosphere alters the spectral signal reaching the sensor. Data collected using imaging spectrometers therefore must be converted from raw radiance values to atmospherically corrected reflectance values to allow spectra to be compared with reference spectra in spectral libraries (Kruse 1994). Ideally, absolute reflectance is calculated, although there are several methods that produce relative reflectance.

Image processing to remove atmospheric effects requires both calibration and atmospheric correction. Calibration adjusts the image by converting raw radiance values to absolute or relative reflection values. Atmospheric corrections then adjust these reflectance values for each pixel and wavelength to adjust for some combination of differing path lengths and effects of atmospheric composition (Table 2).

Calibration uses several methods to convert measured values to relative reflectance or absolute reflectance. Flat field calibration, logarithmic residuals (Green and Craig 1985) and internal average relative reflectance (IARR) (Kruse 1988) produce relative reflectance spectra. Flat field calibration is used to normalize images to an area of known reflectance on the ground. The method divides the ground reference spectra into the image spectra for each band, then uses the resultant ratios to calculate the relative reflectance at each pixel. IARR calibration is used to normalize images to a scene's average spectrum. This is effective for reducing imaging spectrometer data to relative reflectance in an area where no ground measurements exist and little is known about the scene. An average spectrum is calculated from the entire scene; this is then used as the reference spectrum and divided into the measured spectrum at each pixel of the image to estimate relative reflectance. If this method must be used, it operates best in arid areas with no vegetation.

Empirical line calibration and calibration to an atmospheric model are methods for estimating apparent (absolute) reflectance. Empirical line calibration is used to force image data to match selected field reflectance spectra and requires *a priori* knowledge of a site (Conel et al. 1987).

Reference field or laboratory spectra are collected for known locations that cover the full range of spectral variation in the image. Specific pixels from the image are associated with these reference spectra and linear regression is used to calculate the gain and offset needed to convert the digital number for each image band to reflectance. This is equivalent to removing the solar irradiance and the atmospheric path radiance. The instrument digital numbers are then converted to reflectance using the gain and offset values. Of the empirical methods, this produces spectra that are most comparable with field or laboratory spectra.

Calibration to apparent (absolute) reflectance can be made using an appropriate atmospheric model (Gao et al. 1993). The Atmospheric Removal Program (ATREM) (Gao and Goetz 1990) is a radiative transfer model-based method for calibration to absolute reflectance that requires no ground-based measurement. The method was developed for 224 band AVIRIS data. A three channel ratioing method uses the water vapor absorption bands to calculate the amount of water vapour for each pixel. This produces an image of water vapour concentrations. This image is used with transmittance spectra of atmospheric gases to produce scaled surface reflectance. Similarly, MODTRAN, a radiative transfer model (Berk et al. 1998, 1999) can be used to estimate reflectance (Adler-Golden et al. 1998; Gastil and Melack 1998).

A variety of combination methods have also been used. Clark et al. (1995) used a combination of ATREM and the empirical line method to correct model errors in ATREM by calculating normalization factors for one pixel and then applying them to the rest of the ATREM-corrected image. Goetz et al. (1998) combined ground measurements of spectral irradiance with MODTRAN to derive a model equivalent to an empirical line method correction that did not require uniform ground targets of different reflectance. Goetz et al. (1997) and Boardman (1998) also describe an analytical process, the Empirical Flat Field Optimal Reflectance Transformation (EFFORT) that bootstraps a linear adjustment to apparent reflectance spectra to improve the accuracy of spectra from AVIRIS following calibration with ATREM. This improves the comparison with library-based spectra, the basis of many of the image interpretation methods.

The effect of different methods for calibration and atmospheric correction on the characteristic spectral profile for materials is pronounced. Figure 1 shows the raw digital numbers and atmospherically corrected spectral profile for a pixel measured using the Probe1 hyperspectral instrument. Data analysis to identify materials is sensitive to the calibration method used, particularly when generating spectral libraries from imagery, or comparing images to field or laboratory derived reference spectra. Correction using an atmospheric model is recommended since the resulting data can be used with spectral libraries and are comparable for different images.

Data collection considerations: The amount of field effort needed to collect ground-based data for atmospheric corrections varies from nothing to extensive, depending on the algorithm that is used. The IARR method requires no field data, which eliminates field expenses, but at the cost of accuracy. ATREM is far more accurate than the IARR method and requires no field data, but does require an imaging spectrometer that collects narrow band width data in the water vapor absorption bandwidths. Flat field calibration only requires spectral data from one site. Empirical line

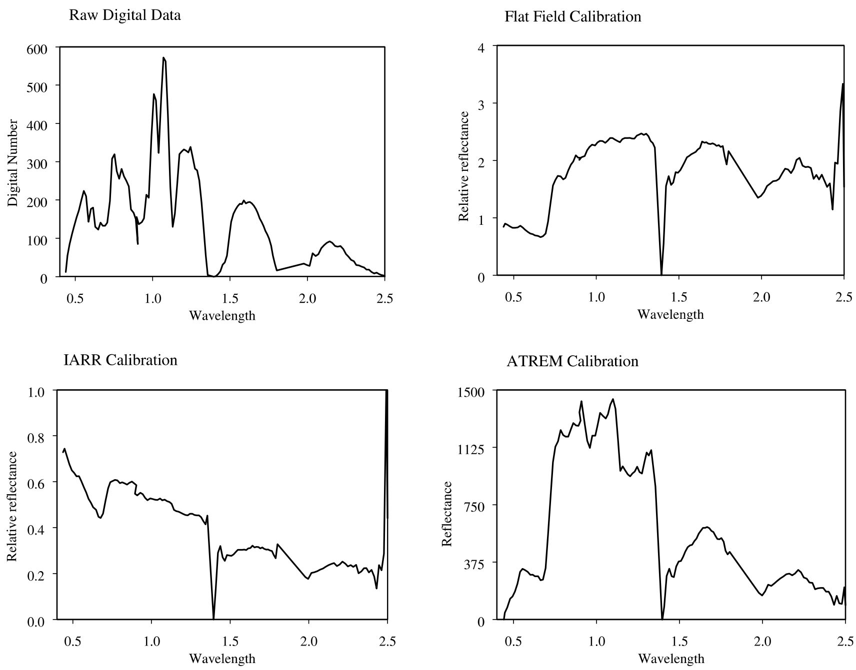

Fig. 1. Probe 1 raw and atmospherically corrected spectral profile

calibration requires a minimum of two ground references sites that represent end members of spectral reflectance, although a number of reference sites along the continuum of reflectance values is preferable. MODTRAN requires extensive ground-based measurements, including RADIOSONDE data to characterise atmospheric thermal structure and water content at different levels.

A number of problems commonly arise with collection of field spectra for atmospheric corrections. Reference targets should be at least 3×3 pixels in size to insure that the center pixel provides a pure signal on the image that is uncontaminated by spectral mixing with adjacent pixels. Finding homogenous features of this size can be difficult, especially in natural settings. Because one is usually trying to collect ground reference data on the day of the flight, one does not have the imagery to guide spectral end member selection for the empirical line approach. Too often one discovers at a later date that the ground sites only represent a portion of the range of spectral reflectances. Finally, the uncertainty in flight timing and difficulties with keeping field teams permanently on alert can mean that there are significant time gaps between ground data collection and image acquisition, which in turn casts doubt on the validity of the ground reference data as a guide to calibrating the image. If ground-based calibrations techniques are going to be used, researchers should therefore spend significant time in the field prior to the flight to locate reference sites that are sufficiently large, that represent light and dark end members, and that are relatively unchanging over time.

Spectral data to develop spectral libraries typically come from laboratory-based spectrometers or portable field spectrometers, all of which are costly to buy or rent and require expert operators. Financial and personnel constraints can thus be a major constraint if equipment and expert operators are not available at reduced cost through research institutes or if existing spectral libraries (Table 3) cannot be used.

4 Geometric Corrections

Analytical approaches: Most hyperspectral imaging systems record spectra using cross track or "whisk broom" sensors, which record the complete spectra for one pixel on the ground before moving ("whisking") to the next pixel. This contrasts with along track (or "push broom") sensors that record multiple spatial instances of a particular spectral band at one time and are more akin to an optical photograph in their geometric characteristics.

Since hyperspectral imaging systems collect data pixel-by-pixel as they scan across track perpendicular to the flight line, the ground location of these pixels can jump dramatically from pixel to pixel due to the pitch, yaw and roll of the aircraft coupled with the cross track scanning of the instrument. Geometric correction of hyperspectral imagery is therefore important in order for the data to be referenced to real world locations and to be used with other spatially referenced data sets. This presents three issues for geometric correction. First, the overall geometry of the imagery is variable since each pixel is collected separately. Standard geometric correction techniques (using n-term polynomial or rubber sheet warping with control points to register images to ground coordinates) is inappropriate and usually unsuccessful (Clark et al. 1998). Second, the pixels may be of variable spatial dimension. Third, there may not be complete coverage of the ground surface. In AVIRIS, which was designed for the relatively stable and predictable motion of the ER-2 platform flying at 20 km elevation, the sensor scanning frequency is tuned to the forward motion of the platform and images are spatially continuous with constant pixel size. Airborne hyperspectral instruments in other platforms are sensitive to the motion of the platform (Boardman 1999).

Clark et al. (1998) and Boardman (1999) have presented methods for geometric correction of hyperspectral imagery from on-board navigation devices. Clark et al. (1998) use a series of equations to correct AVIRIS for the motion of the ER-2 platform, although they do not correct for topographic effects (e.g. changes in elevation). Boardman (1999) uses an onboard Global Positioning System/Inertial Navigation System, C-MIGITS-II to obtain x,y,z (from the GPS) and 3-axis attitude data (from the INS) to

Table 3. Reference libraries for spectra

Features in library	Reference	Library source
Minerals	Clark et al. (1993)	http://speclab.cr.usgs.gov
Minerals	Grove et al. (1992)	http://speclib.jpl/nasa.gov
2000 natural and man-made materials		http://speclib.jpl/nasa.gov
Vegetation	Clark et al. (1993)	http://speclab.cr.usgs.gov

develop and apply a full photogrammetric camera model for low altitude AVIRIS data. The model uses ray-tracing to locate each pixel on the ground surface, a digital elevation model providing ground elevation data. The output is ortho-corrected with full (x,y,z) geo-referencing for each pixel (Boardman 1999). This method has potential for application to any hyperspectral image data, provided GPS/INS data are collected at a frequency that matches the scan frequency of the imaging device and can be digitally tied to the imagery using a common time reference.

The ray-tracing technique is a powerful technique that is both accurate and precise. It is also complex, however, and is not presently built into commercial software. Researchers wanting to use the technique must therefore contract through the commercial vendor that developed it. If the ray-tracing technique is not available because of instrument or logistical constraints, one must then choose between less than optimal solutions. If the plane experienced significant turbulence, the standard polynomial transfer functions are particularly inappropriate because they assume linear or curvilinear variations in pixel location across the entire image, when in fact the image locations vary in a non-linear manner. In this case, a local triangulation technique is preferable, with multiple local control points (e.g. trees) being used to segment the image into triangles, with the images within each triangle being stretched to fit that local surface.

Data collection considerations: HSRH imagery poses particularly severe constraints on the geographic precision required to coregister ground-based maps and pixel locations on images. Locational inaccuracies of only 0.5–1 m can lead to mismatches between image pixels and field maps with high spatial resolution data (Wright et al. 2000; Marcus et al. 2001). When supervised classification techniques are used, this mismatch of image pixels and ground features associates the wrong spectra with ground features, which in turn generates significant inaccuracies in image classification.

Avoiding these mismatches is particularly difficult with HSRH imagery. Even if the image is georeferenced to ± 2 m using the ray-tracing approach, it is difficult to locate features on the ground with this degree of accuracy, especially in natural settings without bench marks, intersections, and features that have well identified point locations. Considerable pre-flight planning should therefore be devoted to considerations of image and map overlay.

The optimal and most accurate approach to precise coregistration of imagery and maps is to map directly to the imagery, using the imagery like an air photo. This is not possible in many cases, however, because researchers often want to map as close to the flight date as possible to insure that mapped features (e.g., stream depths, vegetation cover, soil moisture, etc.) represent conditions shown on the imagery. Some operators of hyperspectral sensors cannot provide imagery rapidly, while others can have same day turn around under the appropriate circumstances. If mapping directly to imagery is a desired method, users should query sensor operators about the turn around time that is required and make this part of the data contract.

Precision location can also be accomplished by placing targets in the field that show up clearly on images. This works well for marking the corners of sample grids or the ends of transects. We have found that 2×2 m plastic ground tarps show up well in natural landscapes with pixel resolutions as large as 5 m. The tarps saturate the pixel spectra, particularly in near infrared bands where the plastic reflectance is radically different than the natural background materials.

One can also do precision mapping using classic field survey equipment or GPS. Unless ground truth sites exist that cover many pixels, however, we do not recommend this approach. Ground map precisions as tight as $+0.5$ m challenge GPS and survey techniques unless field teams are willing to expend significant time, which in turn limits the amount of ground data that can be collected. Second, even with sub-meter precision and accuracy in the ground map, it is almost impossible (even with ray-tracing) to generate comparable precision in the image, unless meter scale DEMs are available. Coregistration of imagery and field maps may therefore still be inaccurate. To overcome this problem, ground truth sites that cover many pixels should be mapped. This allows boundary pixels where overlap errors occur to be discarded from overlay analysis. Unfortunately, many features (e.g., a particular vegetation type such as willows) may not cover multiple pixels even on HSRH-imagery.

Finally, with hyperspectral data, it may not be necessary to have precise locations for ground sites. As noted previously, if a feature has a clear spectral signature, the feature can be detected using spectral matching techniques discussed below. Given the severe coregistration problems associated with HSRH-imagery, this spectral matching approach should be seriously considered as an alternative to supervised classification whenever hyperspectral data are available.

5 Data analysis

Hyperspectral imagery presents a number of opportunities for interpretation and analysis and can make use of methods beyond the standard statistically-based image classification methods used in multi-spectral remote sensing. Multispectral images are often analysed using multivariate statistical classifiers that treat individual wavebands in the imaging instrument as a series of independent variables. These “standard” methods for image classification can be applied to hyperspectral imagery although statistical classification of high-dimensional data that exhibits correlation between spectral bands fails to take full advantage of the key feature of the imagery, namely that it provides access to a measurement of a near complete spectrum for each pixel using narrow wavebands. The data provided by calibrated hyperspectral imagery are comparable with laboratory spectra measured for materials. These reference spectra provide digital ‘lookup’ keys to the composition of pixels and provide a direct measurement of the material being sensed.

A number of specialised methods have been developed to take advantage of the characteristic spectra of materials and there are several reference spectral libraries that provide descriptions of the spectra of materials (Table 3). Further libraries tailored to specific applications of hyperspectral imagery are needed to complement the libraries organised around classes of materials. For example, for health related applications, libraries may be developed that contain spectra for characteristics of habitats that are known to have a close association with vectors of diseases. Kitron et al. (1996) use Landsat Thematic Mapper data and GIS to investigate the distribution of tsetse flies in Kenya and the approach could be extended to hyperspectral imagery with appropriate spectral libraries. Analysis of hyperspectral imagery usually requires an empirical match to be made between the image spectra and a set of reference spectra (end-members) from a spectral library for known materials. Reference spectra can be measured in the laboratory or field; they may also be derived from the hyperspectral imagery itself.

Analysis methods focus either on a) classifying each pixel into a single class by identifying the main material in the pixel, or b) estimating the composition of a pixel using an un-mixing method that identifies multiple materials and their relative abundance within a pixel.

5.1 Single feature identification

There are four main methods for identifying single feature types within hyperspectral imagery:

a) binary encoding,
b) continuum removal,
c) spectral angle mapper, and
d) spectral feature fitting.

Binary encoding: Binary encoding (Mazer et al. 1988) is a classification method that encodes the image data and reference spectra into 0 s and 1s based on whether a band falls below or above the spectrum mean. An exclusive OR function is then used to compare each encoded reference spectrum with the encoded image spectra and classify the image. Each pixel is classified to the material with the greatest number of bands that match, above a minimum match threshold.

Continuum removal: Continuum removal normalizes reflectance spectra to allow comparison of individual absorption features from a common baseline (Kruse et al. 1985; Clark et al. 1987; Kruse et al. 1993a). A convex hull that is fitted to the spectrum describes the continuum. Straight-line segments connect local spectra maxima to define the convex hull, the first and last spectral data values being on the hull by definition.

Spectral angle mapper: The Spectral Angle Mapper (Kruse et al. 1993b) matches pixel spectra to reference spectra using a measure of spectral similarity based on the angle between the spectra treated as vectors in an n-dimensional space with dimensionality, n, equal to the number of image bands. Smaller angles represent closer matches. The angle between each pixel and all reference spectra can be mapped and pixels assigned to the material for which the spectral angle is smallest and within a defined limiting angle. When used on calibrated reflectance data, the spectral angle mapper is relatively insensitive to effects of illumination and albedo since the angle between vectors is measured rather than the length of the vector.

Spectral feature fitting: Spectral Feature Fitting uses least squares methods to compare the fit of image spectra to selected reference spectra (Clark et al. 1990, 1991; Crowley and Clark 1992; Swayze and Clark 1995). Reference spectra are scaled to match the image spectra after continuum removal from both data sets. The method measures absorption feature depth which is related to material abundance.

5.2 Un-mixing methods

Un-mixing methods take advantage of the high-dimensionality of the hyperspectral data to identify sub-components of the spectrum for each pixel. These methods identify the relative contribution of different materials to the spectral composition of a given pixel. They thus provide the capability to map sub-pixel features and abundance of different materials. There are three main methods for un-mixing:

a) matched filtering,
b) spectral un-mixing/spectral mixture analysis, and
c) mixture tuned matched filtering.

Matched filtering: The Matched Filtering method is described by Harsanyi and Chang (1994) and Boardman et al. (1995). Matched filtering performs a partial un-mixing of spectra to estimate the abundance of user-defined end-members from a set of reference spectra. Matched filtering does not require knowledge of all the end-members within an image scene and can also be used to identify single feature types.

Spectral un-mixing/spectral mixture analysis: Spectral un-mixing (Boardman, 1989, 1993) determines the relative abundance of materials based on the spectral characteristics of materials. Reflectance in each image pixel is treated as a linear combination of the reflectance of each end-member present within the pixel. The number of end-members must be less than the number of spectral bands and all of the end-members represented in the image must be used. Boardman (1989) applies singular value matrix decomposition to un-mix hyperspectral data. Spectral libraries provide the initial data matrix to this method.

Mixture tuned matched filtering: Boardman (1998) describes mixture tuned matched filtering (MTMF), a method that builds on the strengths of matched filtering and spectral un-mixing. MTMF combines the ability to map a single known target without knowledge of all end-member signatures with the leverage of mixed pixel models including constraints on feasibility. MTMF also reduces the incidence of false positives.

6 Opportunities for spatial analysis of high spatial resolution hyperspectral imagery

The methods described for analysis of hyperspectral imagery identify materials based solely on the analysis of spectra. The spatial component of hyperspectral imagery offers an additional feature of the data with potential for application in interpretation and mapping of landscape objects. Spatial analysis may help in at least two ways. First, the spatial structure of spectral information in imagery can be used to augment spectral based analysis. Pinzon et al. (1998) and other papers in this issue address the use of spatial analysis as a complement to spectral analysis. Second, spatial analysis may be used to interpret the distribution of materials identified from the imagery by spectral analysis to map and model environmental objects of interest.

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