HYPERSPECTRAL REMOTE SENSING

Introduction

Hyperspectral remote sensing is one of the advance technology which began in early 1980s is one of the most significant breakthroughs in remote sensing. It emerged as a promising technology in remote sensing for studying earth surface materials by two ways spectrally & spatially.In this technology imaging and spectroscopy is combinedin a single system so this is also known as imaging spectroscopy. This technology is developed by breaking a broad band from the visible and infra-red into hundreds of spectral parts to obtain geochemical information from inaccessible planetary surfaces. Hyperspectral remote sensing is able to provide a high level of performance in spectral & radiometric calibration accuracy in the data sets. These high performing sensors data can be utilized for extracting information in various quantitative and qualitative applications. The ample spectral information provided by hyperspectral data is able to identify and distinguish spectrally similar materials which enhance the capability of distinguishing various ground objects in detail. Hyperspectral sensorscollect information as a series of narrow and contiguous wavelength bands at 10 to 20 nm intervals. The spectra for a single pixel in hyperspectral data appears similar like a laboratory quality spectra collected by a spectro-radiometer which can be used for understanding the spectral characteristics of the material.

Principle of Imaging Spectroscopy

As Hyperspectral Remote sensing technology is also known as *Imaging Spectroscopy* which is considered to be as combination of three following photonic technologies:

- *(i)* conventional imaging,
- *(ii)* spectroscopy, &
- *(iii)* radiometry

Above three technologies are used to produce images for which a spectral signature is associated with each pixel. The position of imaging spectroscopy and other related technologies is shown in Figure 1. The datasets produced by hyperspectral imager is in the form of a three dimensional datacube in which two dimensions represents spatial information and third dimension represents spectral information. The values recorded by Spectral Imager Instrument can be converted, via proper calibration, to radiometric quantities that are related to the scene phenomenology (e.g., radiance, reflectance, emissivity, etc.). This technology is having capability to support various applications by providing a link to spatial and spectral analytical models, spectral libraries, etc.

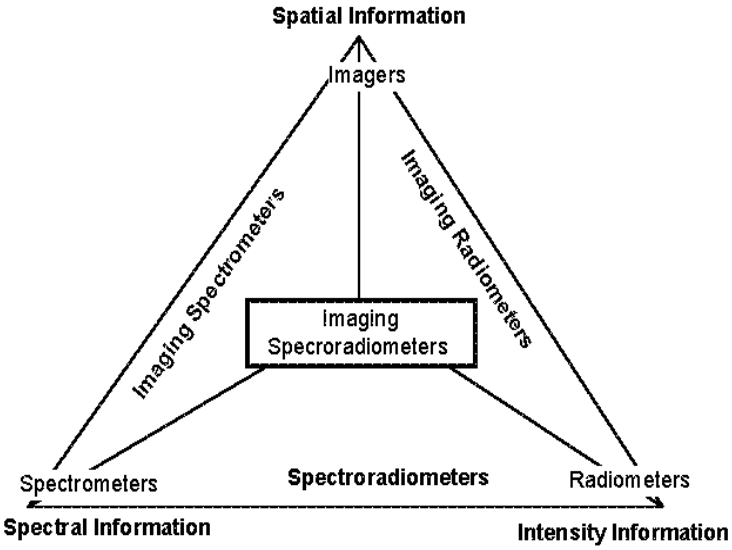


Figure 1. Relationship among Radiometric, Spectrometric, and Imaging Techniques (Elachi 1987)

Spectroscopy depends on the pretext that different materials are different because of the difference in their constituents & structure and because of that they interact differently with light so they appear different. The aim of *Imaging Spectroscopy* is to understand the Earth's surface through the detailed analysis of its reflected light, exploiting subtle variations in surface composition and structure in support of real-world requirements. For spectroscopic study, hyperspectral data sets provide ample spectral detail to discern the subtle differences in color distributions from Earth surface materials. Because Earth's surface is populated with the molecules of the solids and liquids and having characteristic spectral features generally wider than some tens of nanometers, which establishes a practical definition for the maximum spectral band size for a hyperspectral data set.

The reflectance spectra of most of the Earth's surface materials contain characteristic or diagnostic absorption features in the spectral range of 400 to 2500 nm. Since these diagnostic features are typically of a very narrow spectral appearance, those surface materials can be identified directly, if the spectrum is sampled at sufficiently high spectral resolution which becomes possible using imaging spectrometers. There are three types of main absorption features found generally in the spectral range of 400 to 2500 nm regions which should be understood to realize the requirement of hyperspectral imaging system.

a. **Charge transfer absorptions:** These types of absorptions are caused by light at certain wavelengths causing electrons to be transferred between atoms and generally occur in the visible region of the spectrum, and. For example: Fe^{3+} and Fe^{2+}. Light at the proper wavelength causes an electron to be transferred from a Fe^{2+} atom to a Fe^{3+} atom and due to that rusty objects appear red. Detection of this type of absorption is easy as they are quite broad, so it is possible to detect thoseusing conventional multispectral sensors. Asthere is overlap among the absorptions caused by different atoms, so Hyperspectral sensors are required to tell them apart.

b. **Electron transition absorptions**: In atoms with an incomplete electron shell, light at the proper wavelength can bump electrons into different positions in the shell. These absorptions tend to be narrower than the charge transfer absorptions, and the type of atom and the position and variety of its neighbors controls the wavelengths of the absorptions. This feature is especially useful in geology, where the arrangement of atoms in a mineral is very well defined. Since subtle variations in the position of the band centre are important, it is necessary to have many narrowly spaced bands to take advantage of this feature.

c. **Vibrational absorptions**: When light at the same wavelength as a molecule (or part of a molecule) strikes the molecule, it causes the molecule (or part of the molecule) to vibrate. This leads to light absorption. In general these absorptions are very narrow, although their widths and depths vary. Many of the absorptions seen in the 0.4 to 2.5µm region actually originate at longer wavelengths, and what we are seeing are combinations and overtones of the original wavelength. Most of these absorptions can be detected with a multispectral sensor.

Actual detection of materials is dependent on the spectral coverage, spectral resolution, and signal-to-noise ratio of the spectrometer, the abundance of the material and the strength of absorption features for that material in the wavelength region measured. Most natural Earth surface materials have diagnostic absorption features in the 400 -2500 nm range of the reflected spectrum. Since the diagnostic features for each material are apparent over very narrow spectral bands, differences between materials can only be identified if the spectrum is sampled at a sufficiently high resolution. The benefit of hyperspectral remote sensing is that the information about the ground objects can be recorded in a very narrow spectral range hence minute alterations can be mapped.

Multispectral Vs Hyperspectral

Multispectral datasets are produced by sensors which record reflected electromagnetic energy within some specific sections orbroad bands of the electromagnetic spectrum. These Sensors usually produce 3 to 10 number of spectral bands which ranges from visible to near infrared region. However, the spectral resolution and mineral discrimination power is very low. Example of multispectral satellite sensors are Landsat, Spot and IRS satellites.

Hyperspectral sensors measure energy in narrower and more numerous bands than multispectral sensors. Hyperspectral data contains100s or more narrow contiguous spectral bands. The numerous narrow bands of hyperspectral sensors provide a continuous spectral measurement across the entire electromagnetic spectrum and therefore are more sensitive to subtle variations in reflected energy.

Images produced from hyperspectral sensors contain much more data than images from multispectral sensors and have a greater potential to detect differences among land and water features. Hyperspectral sensors are having capability to detect and distinguish individual absorption bands in mineral deposits, vegetation and man-made materials. This discrimination is achieved by spectral sampling at approximately 10 nm intervals across the spectrum.

Multispectral images can be used to map forested areas, while hyperspectral images can be used to map tree species within the forest.

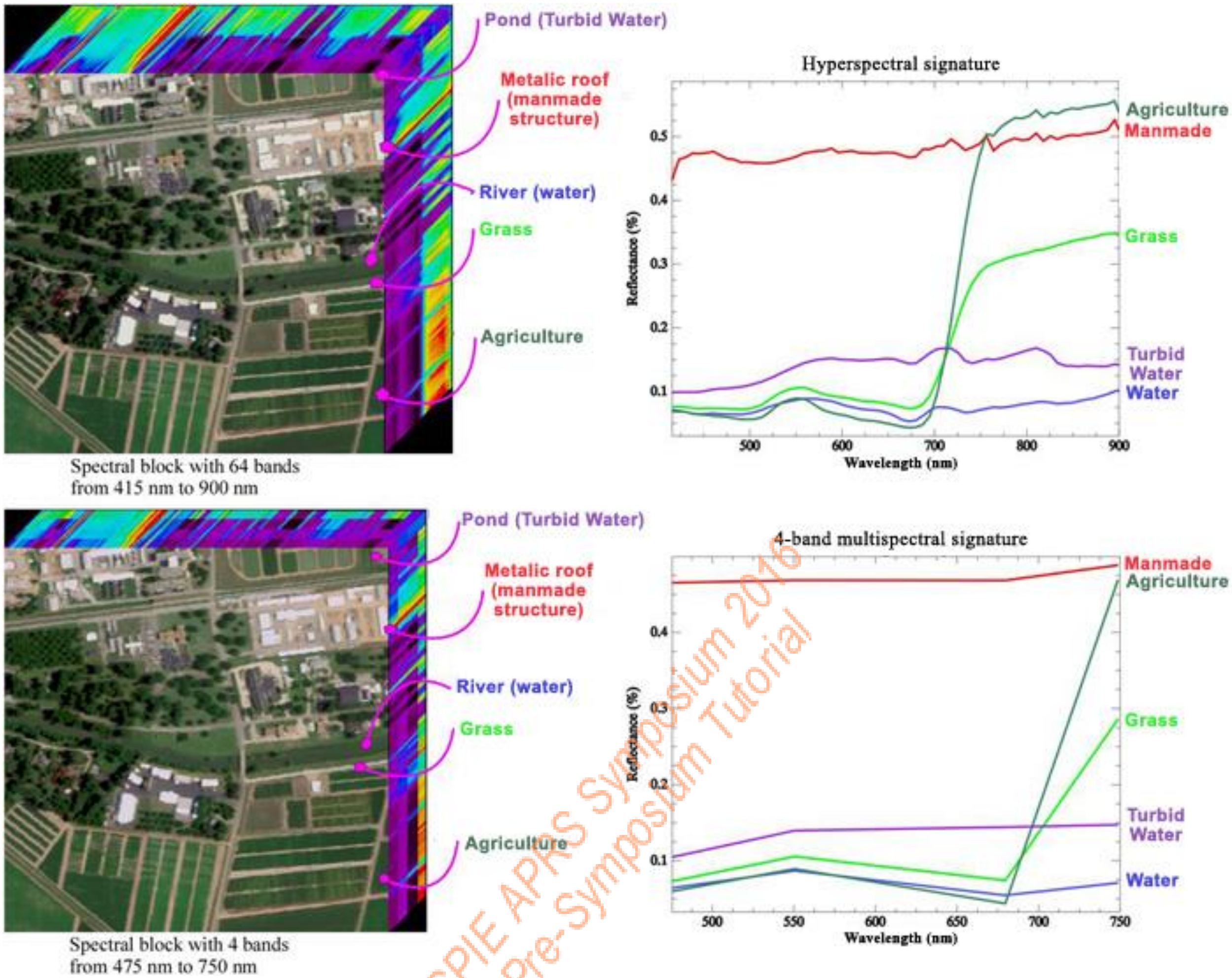


Figure 2. Comparison between hyperspectral and multispectral sensors (*source:ITRES)*

Hyperspectral Data

Hyperspectral remote sensing data sets are generally represented as a data cube with spatial information collected in the X-Y plane, and spectral information represented in the Z-direction. The hyperspectral data sets are composed of about 100 to 200 narrow and contiguous wavelength bands at bandwidths of about 5-10 nm. The spectra for a single pixel in hyperspectral data appears similar like a laboratory quality spectrawhich can be used for understanding the spectral characteristics of the material.Due to the ample spectral information provided by hyperspectral data it is easy to identify and distinguish spectrally similar materials.

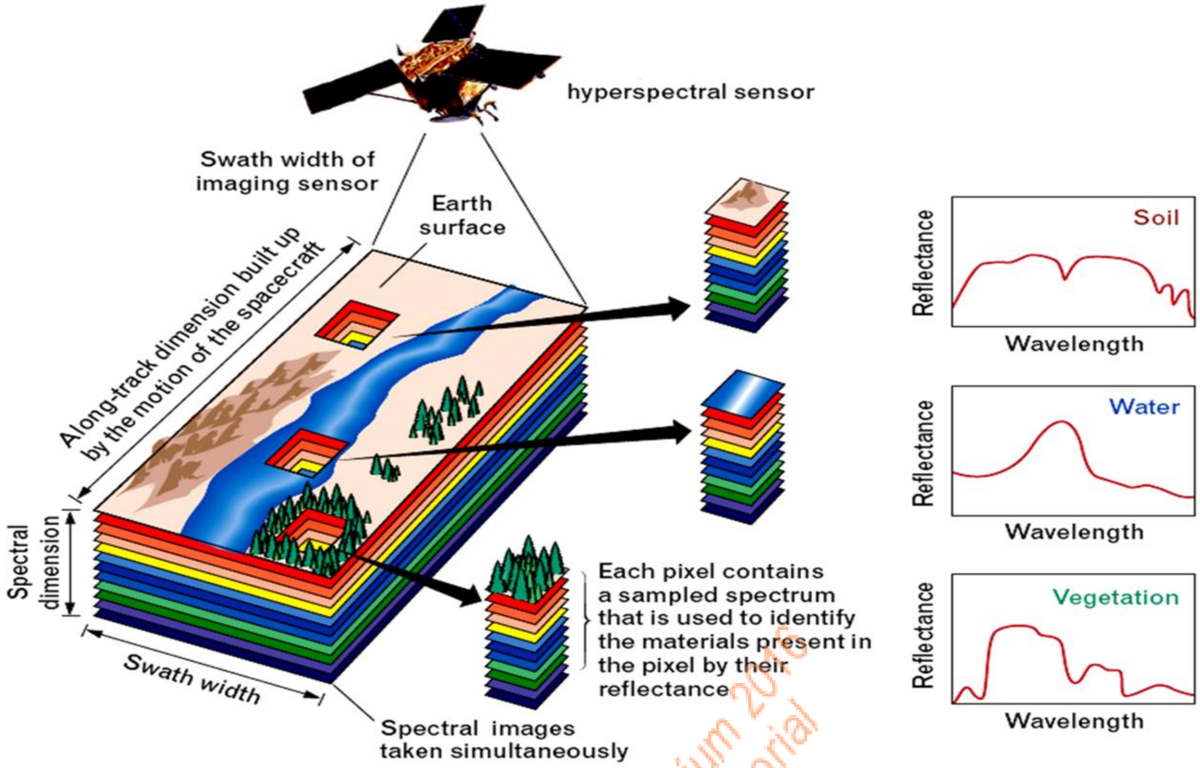


Figure 3. Hyperspectral Remote Sensing (*Source*: NEMO)

Hyperspectral Remote Sensing Sensors

Now-a-days there are many ground-based and airborne hyperspectral sensors but very few spaceborne hyperspectral sensors are available. Various airborne and spaceborne hyperspectral sensors developed by several space agencies national & international are in Table 1 & Table 2:

Table 1: Airborne Hyperspectral Sensors

Sensor	**Spectral coverage (nm)**	**No. of Bands**	**Band width (nm)**	**Spatial Resolution (m)**	**Image tech**	**Country**	**Launched /developer**
GERIS(Geophysical Environment Research Imaging Spectrometer II)	400 - 1000 1400 - 1800 2000 - 2500	24 7 32	25.4 120.0 16.5	1-10	Whisk broom	USA	1987/GRE corp.
AVIRIS(Airborne visible infrared imaging spectrometer)	380-2500	220	10	5-20	Whisk broom	USA	1987/JPL
CASI(Compact Airborne Imaging Spectrometer)	400-800	288	1.8	30	Pushbroom	Canada	1988/ITRES research Ltd
DAIS (Digital Airborne Imaging Spectrometer)	400-1200 1500-1800 2000-2500	72	15-30 45 20	1-10	Pushbroom	Europe	1995/GRE corp.

HYDICE(Hyperspectral Data Image Collection Experiment)	400 - 2500	10.2	210	3	Whisk broom	USA	1996/Naval research lab
HyMAP	400 - 2500	16	125	3-5	Whisk broom	Australia	HyVista Corp
AisaEAGLE	400 - 970	5	200	<1			Spectir Corp

Table2:Spaceborne Hyperspectral sensors

Sensor	**Spectral coverage (nm)**	**No. of Bands**	**Band width (nm)**	**Spatial Resolution (m)**	**Swath (km)**	**launch Year**	**Agency**
Moderate Resolution Imaging Spectrometer (MODIS)- AQUA	400 - 800	32		250-1000	1500	May 2002	NASA
MODIS- TERA	800 - 1455	36		250-1000	2300	Dec 1999	
MERIS (Medium Resolution Imaging Spectrometer)	410to1050	15	10	Ocean: 1040x 1200, Land & coast: 260 x 300	1150		ESA
Hyperion on EO-1	400-2500	220	10	3	7.5	Nov 2000	NASA
CHRIS (Compact High Resolution Imaging Spectrometer on PROBA-1)	438 -1035	18-64	1.25-11	18-36	14-18	Oct 2001	ESA
HySI(Hyperspectral Imager) on IMS-1	400 - 950	64	<15	550	128	Apr 2008	ISRO
Extraterrestrial hyperspectral sensors							
Chandrayaan-1 HySI	400 - 920	64	15	80	20	2008	ISRO
Chandrayaan-1 M3 (Moon Mineralogy Mapper)	400 - 3000	86	10-40	70-140	40	2008	ISRO
OMEGA(Observatoire pour la Mineralogie, l'Eau, le Glace e l'Activite)	360 to5100		7-20	300-4000	8.8		NASA
CRISM (Compact Reconnaissance Imaging Spectrometer for Mars)	362-3920	545	6.55	15.7 to 19.7	9.4 - 11.9		NASA

Hyperspectral Data Processing

For effective utilization of Hyperspectral sensors data sets, different kind of processing and analyzing techniques are required for various applications. All the Hyperspectral sensors developed have enabled generation of remotely sensed laboratory spectra of various materials such as rocks, soils, plants, snow, ice, water and man-made materials. These laboratory quality spectra have been used to obtain compositional information of the earth surface as they are able to detect absorption features caused by minerals in visible, SWIR and TIR region of electromagnetic spectrum. AVIRIS sensor by NASA JPL has been used especially for the mapping of cations and anion for identification of various minerals and rocks. The large amount of spectral information in hyperspectral data is useful for species level discrimination by identifying components unique to certain species of plants. This hyperspectral technology also provides a means for optical oceanographers to classify and quantify complex oceanic environments.

Data Pre-Processing Techniques

The processing of the hyperspectral data sets are more complex as it contains large number of spectral bands which results in larger data volume. The hyperspectral data quality is also affected by the random sensor errors and noise which causes low signal to noise ratio. These data sets are also affected by atmospheric errors, so preprocessing of hyperspectral data is required, pre-processing includes sensor & atmospheric error removal and image rectification.

Sensor error correction

Most of the hyperspectral sensors like Hyperion are pushbroom scanners in which poorly calibrated detectors produces vertical bad lines on the image. Due to the poor calibration the bad lines is having different values then neighboring pixels either the values are constant or lower than the neighboring values. These bad lines can be corrected by replacing their DN values with the average DN values of their immediate left and right neighboring pixels because of the high spatial correlation.

Atmospheric correction

The atmosphere scatters some of the electromagnetic energy which travels from the sun to the Earth’s surface and from Earth’s surface to the sensor. Therefore, the electromagnetic energy received at the sensor may be more or less than that due to reflectance from the earth’s surface alone. Atmospheric correction attempts to minimize these effects on image spectra. Atmospheric correction is traditionally considered to be indispensable before quantitative image analysis using hyperspectral data. Various atmospheric correction algorithms have been developed to calculate concentrations of atmospheric gases directly from the from hyperspectral data. Atmospheric correction is divided into two types: Relative and absolute methods.

1.Relative method is divided into three types

- **a.** Flat field correction
- **b.** Empirical line correction
- **c.** Internal apparent relative reflectance correction

2.Absolute atmospheric correction. This method is based on some atmospheric correction models which require the information regarding the atmospheric condition, altitude, geometry between sun and the satellite, aerosol level, water absorption, time of acquisition of the image and more details. The absolute atmospheric correction methods have the advantage over other methods that these can be run under any atmospheric condition. Some of them are

a. **FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes);** an atmospheric correction modeling tool in ENVI for retrieving spectral reflectance from hyperspectral radiance images. FLAASH incorporates the MODTRAN 4 radiation transfer model to compensate for atmospheric effects.

b. **ATCOR (Atmospheric and Topographic CORrection):** ATCOR algorithm has been developed in the last decade in two different types (ATCOR 2 and ATCOR 3) which are created by Dr. Richter of the German Aerospace Center - DLR. For nearly horizontal surface or flat terrain, ATCOR 2 is a spatially-adaptive fast atmospheric correction algorithm, whereas, ATCOR 3 is designed for rugged topographical surface, hence a Digital Elevation Model (DEM) is used in the ATCOR 3 algorithm for atmospheric correction.

c. **ATREM (Atmospheric REMoval Program):** ATREM is software developed by the University of Colorado for retrieving scaled surface reflectance from hyperspectral data using a radiative transfer model.

d. **ACORN (Atmospheric CORrection Now):** The Atmospheric CORrection Now (ACORN) software package provides an atmospheric correction of Hyperspectral and Multispectral data measured in the spectral range from 350 to 2500 nm. It is also based on MODTRAN 4 radiative transfer code.

Data Dimensionality Reduction

Although, the hyperspectral data are both voluminous and multidimensional, nowadays with the availability of advanced computing systems that possess high speed processors and enormous storage power, data volume is no longer a constraint. The problem lies in the data redundancy that needs to be removed to obtain the bands with maximum information.

Much of the data does not add to the inherent information content for a particular application, even though it often helps in discovering that information; it contains redundancies. The data recorded by hyperspectral sensors often have substantial overlap of information content over the bands of data recorded for a given pixel. In such cases, not all of the data are needed to characterise a pixel properly, although redundant data may be different for different applications. Data redundancy can take two forms; spatial and spectral. Since hyperspectral imagery has more spectral concern, one way of viewing spectral redundancy in hyperspectral data is to form the correlation matrix for an image; the correlation matrix can be derived from the covariance matrix. High correlation between band pairs indicates high degree of redundancy. For example, PCT (Principal Component Transformation) assist in removing redundancy since decorrelation followed by a discarding of low variance components amounts to redundancy reduction.

Probably the most common approach is to employ some sort of linear transformation on the original dataset to produce a smaller set of factors or components. Most of the original variance is retained with a significant reduction in data volume.

Principal Component Analysis (PCA)

PCA transform multidimensional image data into a new, uncorrelated co-ordinate system or vector space. It produces a space in which the data have maximum variance along its first axis, the next largest variance along a second mutually orthogonal axis and so on. Sometimes even the lower-order PC's may contain valuable information. The later principal components would be expected, in general, to show little variance. These could be considered therefore to contribute little to separability and could be ignored, thereby reducing the essential dimensionality of the classification space and thus improving classification speed . Stated differently, the purpose of this process is to compress all the information contained in an original *n* – band data set into fewer than *n* “new bands” or *components* . The components are then used in lieu of the original data. These transformations may be applied as a preprocessing procedure prior to automated classification process of the data.

Minimum Noise Fraction (MNF)

The bands in a hyperspectral dataset have differing noise levels (S/N). It may be desirable to filter or remove those bands that contribute most to noise. When the bands of a hyperspectral dataset have differing amounts of noise, a standard principal components (PC) transform will not produce components with a steadily increasing noise level. This makes it difficult to select a cutoff point. To achieve a components dataset that does have increasing noise (decreasing S/N), a modified PC transform, termed the Minimum Noise Fraction (MNF) has been developed (Green et al. 1988, Lee et al. 1990).

This transformation is mainly used to reduce the dimensionality of hyperspectral data and developed as an alternative to PCA. It is defined as a two-step cascaded PCA. The first step, based on an estimated noise covariance matrix, is to decorrelate and rescale the data noise, where the noise has unit variance and no band-to-band correlations. The next step is a standard PCA of the noise-whitened data.

The MNF transformation is a linear transformation related to PC that orders the data according to signal-to-noise-ratio. It determines the inherent dimensionality of the data, segregates noise in the data and reduces the computational requirements for subsequent processing. It partitions the data space into two parts: one associated with large eigenvalues and coherent eigenimages, and a second with near-unity eigenvalues and noise-dominated images. By using only the coherent portions in subsequent processing, the noise is separated from the data, thus improving spectral processing results.

Ground/Laboratory Spectra Acquisition

Ground based/laboratory spectra acquisition is required to serve various purposes in the context of hyperspectral data acquisition and analysis. The purpose of collection of Ground based/laboratory spectra are for

- providing critical information for calibration of data and atmospheric correction,
- providing spectral library for identification of materials and comparison with the results with hyperspectral data, and
- validation of mapping results obtained using hyperspectral data.

Calibration and Atmospheric Correction

For obtaining accurate results calibrating and atmospheric correction is a requirement for most hyperspectral data analysis process. The identification and mapping of materials and material properties is best accomplished by deriving the fundamental properties of the surface, its reflectance, while removing the interfering effects of atmospheric absorption and scattering, the solar spectrum, and instrumental biases. Calibration to surface reflectance is inherently simple in concept, yet it is very complex in practice because atmospheric radiative transfer models and the solar spectrum have not been characterized with sufficient accuracy to correct the data to the precision of some currently available instruments, such as the NASA/JPL Airborne Visible and Infra-Red Imaging Spectrometer.

The objectives of calibrating remote sensing data are to remove the effects of the atmosphere (scattering and absorption) and to convert from radiance values received at the sensor to reflectance values of the land surface. The advantages offered by calibrated surface reflectance spectra compared to uncorrected radiance data include: 1) the shapes of the calibrated spectra are principally influenced by the chemical and physical properties of surface materials, 2) the calibrated remotely-sensed spectra can be compared with field and laboratory spectra of known materials, and 3) the calibrated data may be analyzed using spectroscopic methods that isolate absorption features and relate them to chemical bonds and physical properties of materials. Thus, greater confidence may be placed in the maps of derived from calibrated reflectance data, in which errors may be viewed to arise from problems in interpretation rather than incorrect input data.

Spectral Libraries

Spectral Libraries are collections of spectra of different surface materials generated from laboratory & ground based measurement and used as the reference against which hyperspectral imaging data are compared to determine earth surface material’s composition. Spectral libraries contain spectra of individual species, Often grouped by surface type (vegetation vs. soils vs. man-made materials etc.) and sometimes by grain size fraction (influence on spectra) acquired at test sites representative of varied terrain and climatic zones.These are principally used for identification of mineralogy, but also contain some spectra of vegetation, man-made materials, snow-ice, and water. There are a variety of spectral libraries for earth-surface materials available e.g. spectral library included in ENVI software and ASTER speclib on the internet.

Endmember extraction

Theoretically the existing pure features in mixed pixels are refered to as endmembers. Selection and identification of spectral endmembers in an image is the key point to success of the linear spectral mixing model. A set of endmembers should allow the description of all spectral variability for all pixels. Two different approaches have generally been used to define endmembers in a mixing model:

- Use of the existing library of reflectance spectra
- extraction of the purest pixels from the image data itself

Endmembers resulting through the first option are denoted as known endmembers whereas the second option results in derived endmembers. Because of the difficulties of access to spectral library or field measurement of spectral properties of land cover types of interest, endmember data of the known ground cover types can be extracted from the Hyperspectral data.

The Pixel Purity Index (PPI) algorithm for Endmember selection is based on the geometry of convex sets. A dimensionality reduction is first performed using the MNF transform. Next, a pixel purity index is calculated for each point in the image cube by randomly generating lines in the N-dimensional space comprising a scatterplot of the MNF transformed data. All of the points in the space are now projected onto the lines and those ones that fall at the extremes of the lines are counted. After many repeated projections to different lines, those pixels that count above a certain threshold are declared “pure”. These potential endmember spectra are loaded into an N-dimensional visualization tool and rotated in real time until extremities in the data cloud that will likely correspond with scene endmembers are visually identified.

Hyperspectral Data Classification

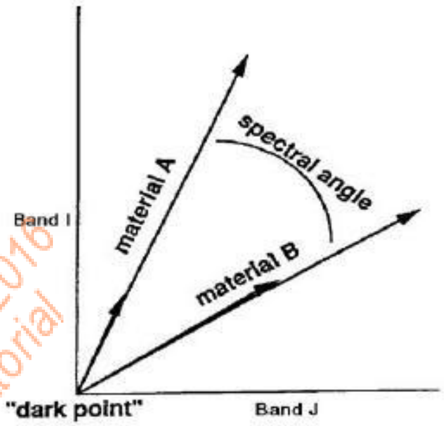
There are many techniques developed for extracting extensive information contained in hyperspectral data Most of these algorithms Spectral analysis methods usually compare pixel spectra with a reference (or target) spectrum. Target spectra can be derived from a variety of sources, including spectral libraries, regions of interest within a spectral image, or individual pixels within a spectral image. The most commonly used method for information extraction using hyperspectral data are

Per Pixel Classification Methods

The Per pixel classification methods attempt to determine the abundances of one or more target materials within each pixel in a hyperspectral data on the basis of the spectral similarity between the pixel and target spectra. These methods include standard supervised classifiers such as Minimum Distance or Maximum Likelihood and classifiers developed specifically for classifying hyperspectral data such as Spectral Angle Mapper and Spectral Feature Fitting.

Spectral Angle Mapper Classification

SAM is an automated method for comparing image spectra to individual spectra or to a spectral library (Boardman, unpublished data; CSES, 1992; Kruse et al., 1993a). SAM assumes that the data have been reduced to apparent reflectance (true reflectance multiplied by some unknown gain factor, controlled by topography and shadows). The algorithm determines the similarity between two spectra by calculating the spectral angle between them, treating them as vectors in n-D space, where n is the number of bands. SAM considers every pixel in the scene and evaluates the similarity of the spectra to repress the influence of the shading, which accentuates the characteristics of reflectance. The image spectrum is then assigned a correlation factor between 0 (low correlation) and 1 (high correlation) and compared to a spectral library or endmember. With SAM, the data are converted to apparent reflectance, which is the true reflectance with gain coefficients that are defined by terrain and lighting conditions.Consider a reference spectrum and an unknown spectrum from two-band data. The two different materials are represented in a 2D scatter plot by a point for each given illumination, or as a line (vector) for all possible illuminations.



Because SAM uses only the direction of the spectra, not the length, SAM is insensitive to the unknown gain factor. All possible illuminations are treated equally. Poorly illuminated pixels fall closer to the origin of the scatter plot. The color of a material is defined by the direction of its unit vector. The angle between the vectors is the same, regardless of the length. The length of the vector relates only to how fully the pixel is illuminated. The SAM algorithm generalizes this geometric interpretation to n-D space. SAM determines the similarity of an unknown spectrum t to a reference spectrum r, by applying the following equation:

$$\alpha = \cos^{-1}\left(\frac{\sum_{i=1}^{nb} t_i r_i}{\left(\sum_{i=1}^{nb} t_i^2\right)^{1/2}\left(\sum_{i=1}^{nb} r_i^2\right)^{1/2}}\right)$$

where nb equals the number of bands in the image.

The spectral angle is the angle between any two vectors originating from a common origin. The magnitude of the angle indicates the similarity or dissimilarity of the materials—a smaller angle correlates to a more similar spectral signature. This method is relatively insensitive to changes in illumination on the target material because changes in light will impact the magnitude but not the direction of the vector. A poorly illuminated target will cause the points to be plotted closer to the origin.

Spectral Feature Fitting

Spectral Feature Fitting is a method developed by the U. S. Geological Survey for analyzing hyperspectral data which is an absorption-feature-based method for matching image spectra to reference endmembers. Most methods used for analysis of hyperspectral data still do not directly identify specific materials. They only indicate how similar the material is to another known material or how unique it is with respect to other materials. Techniques for direct identification of materials, however, via extraction of specific spectral features from field and laboratory reflectance spectra have been in use for many years. At first these techniques have been applied to hyperspectral data for geologic applications.

Prior to analysis this method requires data should be reduced to reflectance and that a continuum be removed from the reflectance data. A continuum is a mathematical function used to isolate a particular absorption feature for analysis. It corresponds to a background signal unrelated to specific absorption features of interest. Spectra are normalized to a common reference using a continuum formed by defining high points of the spectrum (local maxima) and fitting straight line segments between these points. The continuum is removed by dividing it into the original spectrum.

Spectral feature fitting requires that reference endmembers be selected from either the image or a spectral library, that both the reference and unknown spectra have the continuum removed, and that each reference endmember spectrum be scaled to match the unknown spectrum. A "Scale" image is produced for each endmember selected for analysis by first subtracting the continuum-removed spectra from one, thus inverting them and making the continuum zero. A single multiplicative scaling factor is then determined that makes the reference spectrum match the unknown spectrum.

Assuming that a reasonable spectral range has been selected, a large scaling factor is equivalent to a deep spectral feature, while a small scaling factor indicates a weak spectral feature. A least-squares-fit is then calculated band-by-band between each reference endmember and the unknown spectrum. The total root-mean-square (RMS) error is used to form an RMS error image for each endmember. An optional ratio image of Scale/RMS provides a "Fit" image that is a measure of how well the unknown spectrum matches the reference spectrum on a pixel-by-pixel basis.

Sub-Pixel Classification

Sub-pixel analysis methods can be used to calculate the quantity of target materials in each pixel of an image. Sub-pixel analysis can detect quantities of a target that are much smaller than the pixel size itself. In cases of good spectral contrast between a target and its background, sub-pixel analysis has detected targets covering as little as 1-3% of the pixel. Sub-pixel analysis methods include Complete Linear Spectral Unmixing, and Matched Filtering.

Linear Spectral Unmixing

Linear Spectral Unmixing is a means of determining the relative abundances of materials depicted in multispectral imagery based on the material's spectral characteristics. The reflectance at each pixel of the image is assumed to be a linear combination of the reflectance of each material (or endmember) present within the pixel. There are certain limitations that apply for the linear spectral unmixing technique. The number of endmembers must be less than the number of spectral bands and all of the endmembers in the image must be used for an efficient mapping result. Spectral unmixing results are highly dependent on the input endmembers and changing the endmembers will change the results.

Unmixing simply solves a set of *n* linear equations for each pixel, where *n* is the number of bands in the image. The unknown variables in these equations are the fractions of each endmember in the pixel. To be able to solve the linear equations for the unknown pixel fractions it is necessary to have more equations than unknowns, which means that we need more bands than endmember materials. With hyperspectral data this is almost always true. The results of Linear Spectral Unmixing include one abundance image for each endmember. The pixel values in these images indicate the percentage of the pixel made up of that endmember. For example, if a pixel in an abundance image for the endmember quartz has a value of 0.90, then 90% of the area of the pixel contains quartz. An error image is also usually calculated to help evaluate the success of the unmixing analysis.

Mixture tuned matched filtering

Matched Filtering is one of the unmixing type in which user chosen target spectra can be mapped (Boardman et al., 1995). In Complete Unmixing, to get an accurate analysis finding out the spectra of all endmembers from the data are required but this type of unmixing is called a 'partial unmixing' because the unmixing equations are only partially solved. Matched Filtering was originally developed to compute abundances of targets that are relatively rare in the scene. If the target is not rare, special care must be taken when applying and interpreting Matched Filtering results.

Matched Filtering "filters" the input image for good matches to the chosen target spectrum by maximizing the response of the target spectrum within the data and suppressing the response of everything else (which is treated as a composite unknown background to the target). Like Complete Unmixing, a pixel value in the output image is proportional to the fraction of the pixel that contains the target material. Any pixel with a value of 0 or less would be interpreted as background (i.e., none of the target is present). The problem with Matched Filtering is that it is possible to end up with false positive results, but solution to this problem is to calculate an additional measure called "infeasibility". Infeasibility is based on both noise and image statistics and indicates the degree to which the Matched Filtering result is a feasible mixture of the target and the background. Pixels with high infeasibilities are likely to be false positives regardless of their matched filter value.

Mixture-Tuned Matched filter results are presented as two sets of images, the MF score (Matched Filter image), presented as gray-scale images with values from 0 to 1.0, which provide a means of estimating relative degree of match to the reference spectrum (where 1.0 is a perfect match) and the Infeasibility image, where highly infeasible numbers indicate that mixing between the composite background and the target is not feasible. The best match to a target is obtained when the Matched Filter Score is high (near 1) and the infeasibility score is low (near 0).

Hyperspectral Remote Sensing Applications

Hyperspectral data has been used to identify and distinguish spectrally similar materials having characteristic reflectance spectra. Due to the capability of distinguishing various ground objects in detail, hyperspectral datasets are able to detect and map a wide variety of materials.

- **Mineral Targeting:** Spectral reflectance in visible and near-infrared offers a rapid and inexpensive technique for determining the mineralogy of samples and obtaining information on chemical composition.
- **Soils:** Obtaining quantitative information about soil chemistry, its genetic and fertility classification. Study of soil parameters such as organic matter, soil moisture, particle size distribution iron oxide content, soil structure etc. The hyperspectral data with improved radiometric and spatial resolution will help in deriving an improved vegetation/soil indices that will maximize sensitivity to plant biophysical parameters, increase sensitivity to the vegetation signal and normalize atmosphere and ground contamination noise influence.
- **Vegetation:** Study of species diversity, environmental stress, physiological features such as photosynthetic activity, plant productivity, canopy biochemistry, biomass and plant transpiration. Also for evaluation of vegetation stress, nutrient stress, moisture stress and crop growth models.
- **Atmosphere:** Study of atmospheric parameters such as clouds, aerosol conditions and water vapor monitoring, large scale atmospheric variations as a result of environmental change.
- **Oceanography:** Measurement of photosynthetic potential by detection of phytoplankton, detection of yellow substance and detection of suspended matter. It also helps in investigations of water quality, monitoring coastal erosion.
- **Snow and Ice:** Spatial distribution of various types of snow cover, surface albedo and snow water equivalent. Calculation of energy balance of a snow pack, estimation of snow properties-snow grain size, snow depth and liquid water content.
- **Oil Spills:** When oil spills in an area affected by wind, waves, and tides, a rapid and assessment of the damage can help to maximize the cleanup efforts. Environmentally sensitive areas can be targeted for protection and cleanup, and the long-term damage can be minimized. Time sequence images of the oil can guide efforts in real-time by providing relative concentrations and accurate locations

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