

Hyperspectral Remote Sensing

Introduction

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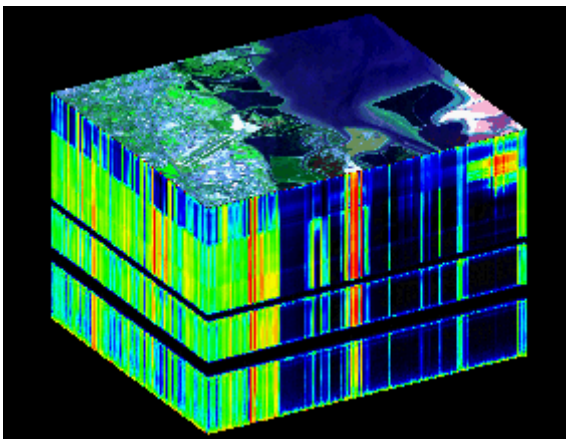
Background Information

Recent advances in remote sensing and geographic information has led the way for the development of hyperspectral sensors. Hyperspectral remote sensing, also known as imaging spectroscopy, is a relatively new technology that is currently being investigated by researchers and scientists with regard to the detection and identification of minerals, terrestrial vegetation, and man-made materials and backgrounds.

Imaging spectroscopy has been used in the laboratory by physicists and chemists for over 100 years for identification of materials and their composition. Spectroscopy can be used to detect individual absorption features due to specific chemical bonds in a solid, liquid, or gas. Recently, with advancing technology, imaging spectroscopy has begun to focus on the Earth. The concept of hyperspectral remote sensing began in the mid-80's and to this point has been used most widely by geologists for the mapping of minerals. Actual detection of materials is dependent on the spectral coverage, spectral resolution, and signal-to-noise of the spectrometer, the abundance of the material and the strength of absorption features for that material in the wavelength region measured.

Hyperspectral remote sensing combines imaging and spectroscopy in a single system which often includes large data sets and require new processing methods. Hyperspectral data sets are generally composed of about 100 to 200 spectral bands of relatively narrow bandwidths (5-10 nm), whereas, multispectral data sets are usually composed of about 5 to 10 bands of relatively large bandwidths (70-400 nm).

Hyperspectral imagery is typically collected (and represented) as a data cube with spatial information collected in the X-Y plane, and spectral information represented in the Z-direction.



AVIRIS hyperspectral data cube over Moffett Field, CA

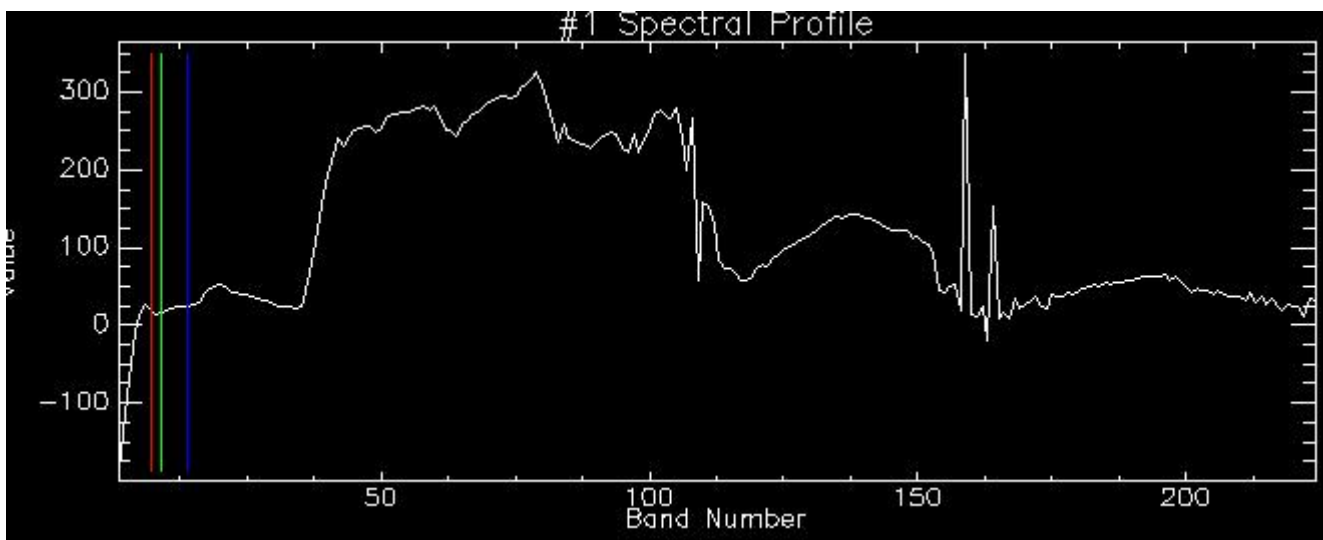
Applications

There are many applications which can take advantage of hyperspectral remote sensing.

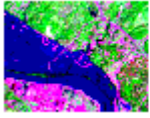
- **Atmosphere:** water vapor, cloud properties, aerosols
- **Ecology:** chlorophyll, leaf water, cellulose, pigments, lignin
- **Geology:** mineral and soil types
- **Coastal Waters:** chlorophyll, phytoplankton, dissolved organic materials, suspended sediments
- **Snow/Ice:** snow cover fraction, grainsize, melting
- **Biomass Burning:** subpixel temperatures, smoke
- **Commercial:** mineral exploration, agriculture and forest production

n-Dimensional Data

Hyperspectral data (or spectra) can be thought of as points in an n-dimensional scatterplot. The data for a given pixel corresponds to a spectral reflectance for that given pixel. The distribution of the hyperspectral data in n-space can be used to estimate the number of spectral endmembers and their pure spectral signatures and to help understand the spectral characteristics of the materials which make up that signature.



Vegetation Spectral Reflectance extracted from AVIRIS data



Processing of Hyperspectral Imagery

Recent advances in sensor technology have led to the development of hyperspectral sensors capable of collecting imagery containing several hundred bands over the spectrum. However, the increase in the number of bands is both a blessing and a curse. The large number of bands provides the opportunity for more materials to be discriminated by their respective spectral response. However, this large number of bands is the characteristic which leads to complexity in analysis techniques. The techniques described in the following sections are those which are widely used by the [USGS](#), [NASA's Jet Propulsion Laboratory](#), [ENVI](#), and others. There are, however, other methods and algorithms to extract information from hyperspectral sensors.

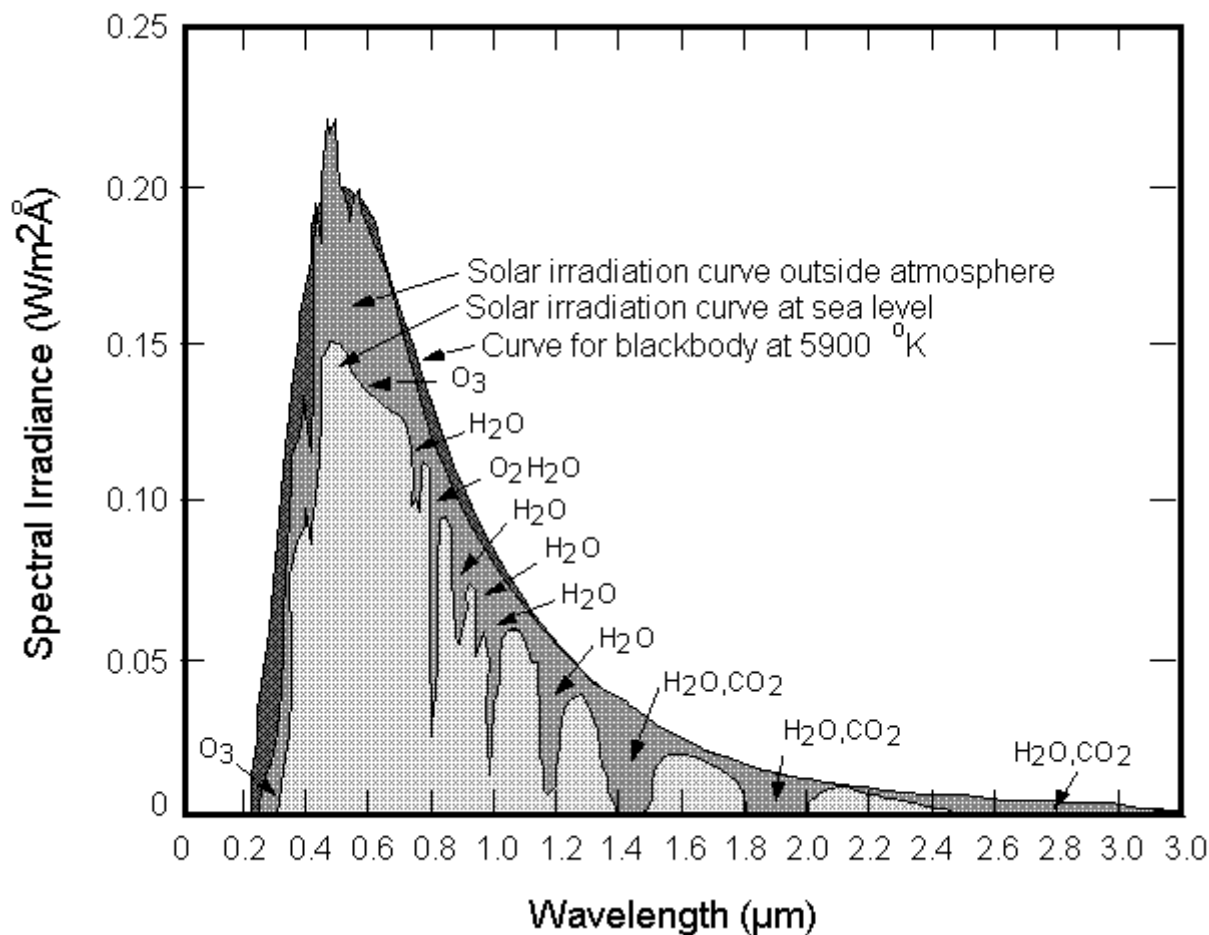
One difficulty in working with hyperspectral data is to understand the differences associated with working in n-dimensional space. One must be careful about using two or three dimensional conceptual truths as a basis for conclusions in higher dimensional spaces [Langrebe, 1997].

Radiometric Correction

Hyperspectral imaging sensors collect radiance data from either airborne or spaceborne platforms which must be converted to apparent surface reflectance before analysis techniques can take place. Atmospheric correction techniques have been developed that use the data themselves to remove spectral atmospheric transmission and scattered path radiance. There are seven gases in the Earth's atmosphere that produce observable absorption features in the 0.4 - 2.5 micron range. They are

- water vapor,
- carbon dioxide,
- ozone,
- nitrous oxide,
- carbon monoxide,
- methane,
- and oxygen.

Approximately half of the 0.4 - 2.5 micron spectrum is affected by gaseous absorption is illustrated below in Figure 1. For this reason, the ATREM 3.0 (Atmosphere Removal Program) developed by the Center from the Study of Earth from Space (CSES) at the University of Colorado can be used to remove the effects of the atmosphere from AVIRIS or HYDICE imagery. ATREM is available via anonymous ftp at [cses.colorado.edu](ftp://cses.colorado.edu/pub/atrem) from the **pub/atrem** directory.



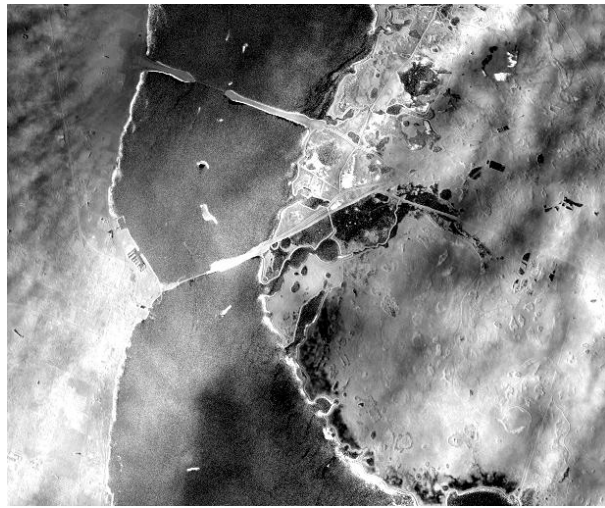
Solar Spectrum with Atmospheric Absorptions

The ATREM software was developed to determine the **scaled surface reflectance** from hyperspectral imagery from both AVIRIS and HYDICE sensors. The atmospheric scattering used by ATREM is modeled after the MODTRAN 5S code. The ATREM software assumes that the surface is horizontal and has a Lambertian reflectance. If topography is known, then the **scaled surface reflectance** can be converted into **real surface reflectance**.

The ATREM model is a good approximation to radiometric correction of the imagery. However, calibration of the ATREM surface reflectance to *in situ* measurements should improve the final results. A by-product from the ATREM software is an image of the columnar water vapor which was removed from the input hyperspectral data. The two figures below represent an AVIRIS frame prior to the ATREM correction and a water vapor scene removed from an AVIRIS scene which was acquired over the Kennedy Space Center on March 23, 1996. The images show a significant amount of water vapor removed from the imagery which causes attenuation of the upwelling radiance.



Original AVIRIS data over KSC (Bands 20, 29, 40)



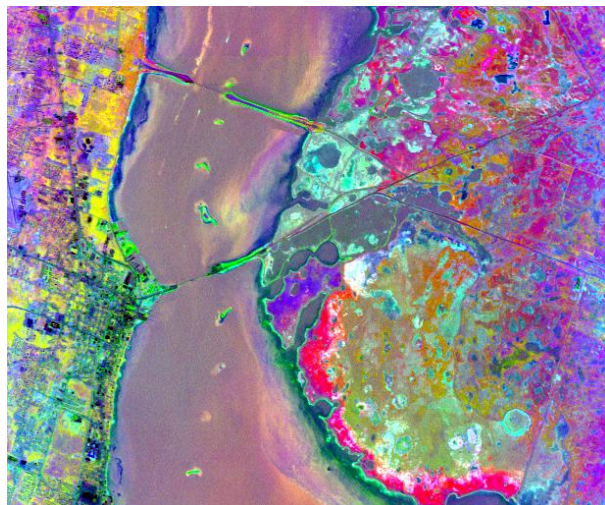
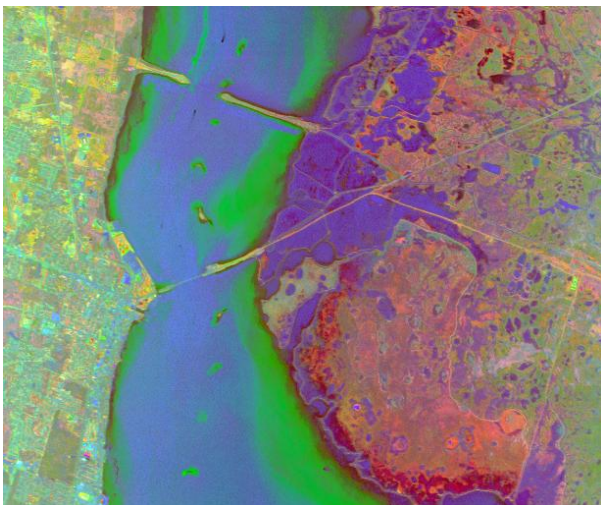
Columnar water vapor image removed from AVIRIS data using ATREM program.

Minimum Noise Fraction (MNF) Transformation

While hyperspectral imagery is capable of providing a continuous spectrum ranging from 0.4 to 2.5 microns (in the case of AVIRIS) for a given pixel, it also generates a vast amount of data required for processing and analysis. Due to the nature of hyperspectral imagery (i.e. narrow wavebands), much of the data in the 0.4-2.5 micron spectrum is redundant.

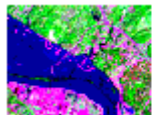
A minimum noise fraction (MNF) transformation is used to reduce the dimensionality of the hyperspectral data by segregating the noise in the data. The MNF transform is a linear transformation which is essentially two cascaded Principal Components Analysis (PCA) transformations. The first transformation decorrelates and rescales the noise in the data. This results in transformed data in which the noise has unit variance and no band to band correlations. [ENVI] The second transformation is a standard PCA of the noise-whitened data.

For this particular example, an AVIRIS frame over the Kennedy Space Center was radiometrically corrected using ATREM and a MNF transformation was performed on the ATREM-corrected imagery. In this particular frame, the first 14 eigenvectors of the MNF transformation contain coherent information which can be used for further processing.



Pixel Purity Index

The Pixel Purity Index (PPI) is a processing technique designed to determine which pixels are the most spectrally **unique** or **pure**. Due to the large amount of data, PPI is usually performed on MNF data which has been reduced to coherent images. The most spectrally pure pixels occur when there is mixing of endmembers. The PPI is computed by continually projecting n-dimensional scatterplots onto a random vector. The extreme pixels for each projection are recorded and the total number of **hits** are stored into an image. These pixels are excellent candidates for selecting endmembers which can be used in subsequent processing.



Analysis of Hyperspectral Imagery

Spectral Angle Mapper Classification

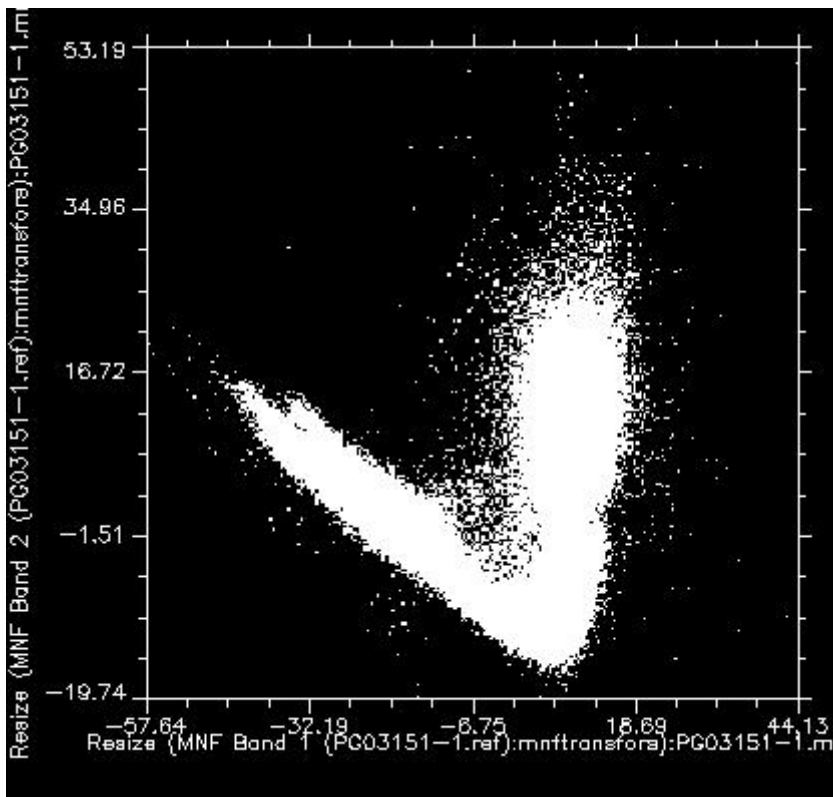
The Spectral Angle Mapper Classification (SAM) is an automated method for directly comparing image spectra to a known spectra (usually determined in a lab or in the field with a spectrometer) or an endmember. This method treats both (the questioned and known) spectra as vectors and calculates the spectral angle between them. This method is insensitive to illumination since the SAM algorithm uses only the vector **direction** and not the vector **length**. The result of the SAM classification is an image showing the best match at each pixel. This method is typically used as a first cut for determining the mineralogy and works well in areas of homogeneous regions. The [USGS](#) maintains a large spectral library, mostly composed of mineral and soil types, which image spectra can be directly compared.

Spectral Unmixing/Matched Filtering

Most surfaces on the earth, geologic or vegetated, are not homogeneous which results in a mixture of signatures characterized by a single pixel. Depending on how the materials are mixing on the surface results in the type of mathematical models capable of determining their abundances. If the mixing is rather large, then the mixing of the signatures can be represented as a linear model. However, if the mixing is microscopic, then the mixing models become more complex and non-linear.

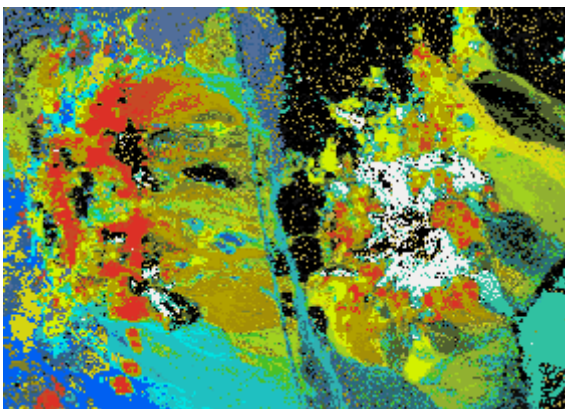
The first step to determining the abundances of materials is to select **endmembers**, which is the most difficult step in the unmixing process. The ideal case would consist of a spectral library which consists of endmembers when linearly combined can form all observed spectra [Kruse et. al, 1997]. A simple vector-matrix multiplication between the inverse library matrix and an observed mixed spectrum gives an estimate of the abundance of the library endmembers for the unknown spectrum.

N-Dimensional visualization techniques can be used to select endmembers within a scene. The image below represents a 2-Dimensional representation of endmember selection using [ENVI](#). Extreme pixels which ultimately correspond to endmembers can be determined by rotating this scatter plot in n-dimensions.



2-Dimensional scatter plot of Eigenvectors 1 & 2.

Matched filtering is based on a well known signal processing method and creates a quick means of detecting specific minerals based on matches to specific library or endmember spectra. The matched filtering algorithm maximizes the response of a known endmember while suppressing the response of the background. The result of the matched filtering resembles the results from the linear unmixing methods and are usually represented as a greyscale image with values ranging from 0 to 1 which corresponds to the relative degree of the match.



Classified image of 1995 AVIRIS frame over Cuprite, Nevada using Spectral Unmixing Techniques

Other Classification Techniques

Classification and feature extraction methods have been commonly used for many years for the mapping of minerals and vegetative cover of multispectral data sets. However, conventional classification methods, such as a Gaussian Maximum Likelihood algorithm, cannot be applied to hyperspectral data due to the high dimensionality of the data.

The difficulty in using many classification methods based upon conventional multivariate statistical approaches, is that many of these methods rely on having a non-singular class-specific covariance matrices for all classes

[Benediktsson et. al, 1995]. When working with high-dimensional data sets, it is likely that the covariance matrices will be singular when using a limited (with respect to the number of input bands) amount of training samples.

A nonparametric classifier, such a neural network, and other feature extraction methods can be used to accurately classify a hyperspectral image. Feature extraction methods, such as the decision boundary feature extraction (DBFE) can extract the features necessary to achieve classification accuracy while reducing the amount of data analyzed in feature space.

Classification of wetland vegetation using AVIRIS data

References

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