The Evolution of Spectral Remote Sensing from Color Images to Imaging Spectroscopy

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Abstract

The spectral remote sensing field has evolved over several decades from color imagery to multispectral imagery to today's imaging spectrometer data. The goal of this evolution was to acquire increasingly detailed information about material types on the earth's surface. The expectation was that adding more spectral bands would add increasing material separability and increasing information about the condition (e.g. water quality or vegetation health) of a given material. This paper will address the extent to which these expectations are being realized (i.e. are 100 bands dramatically better than 3 bands). In addition, the algorithms that have been developed by the remote sensing community for understanding (i.e. unmixing) mixtures of materials based on spectral content are briefly introduced. Finally, the potential to utilize imaging spectroscopy in other applications areas is discussed.

Introduction and Summary

Remote sensing of the earth and the planets has evolved dramatically over the last several decades. Advances in sensor technology and data processing power have enabled the development of analysis tools that have provided increasingly detailed knowledge of the planets surface and environment. Much of this advance has been enabled by the increasing spectral content of the data. Because remote sensing science is driven by and coupled to NASA's space programs and the defense/intelligence community's reconnaissance mission, the field often leads the way in developing new technology and analytical tools. This paper briefly reviews the evolution of spectral remote sensing in the hope that it will motivate practitioners of other fields who may be able to adapt the lessons learned to the characterization of other targets. In particular the fields of machine vision, art conservation, medical imaging and non-destructive testing are beginning to take advantage of some of the early developments in spectral remote sensing.

2. Color Remote Sensing

The early days of remote sensing focused on the use of black and white film and advancements focused on the development of higher resolution and larger format films to support more detailed or larger area photo interpretation. As color film was developed it was put to use in attempts to better characterize the earth.

2.1 Color Sensor and Processing Technology

The color films and cameras used by the remote sensing community were (and are) very similar to the color positive slide films in regular use today. They used three bands (red, green, blue) to attempt to capture and record the color of objects. Technological advances focused on higher spatial resolution, improved color reproduction, higher film speeds (to reduce blurring due to aircraft motion) and larger film and camera format to increase spatial coverage. Color films were initially just analyzed using photo interpretation with the color tones adding increased information about the condition of a material type (e.g., clarity of water, age of asphalt) and spatial patterns used to define material type. With increased interest in quantitative information the idea of using the film camera system as an analytical instrument evolved. Initially this involved developing methods to relate color film density to exposure (i.e. to remove film nonlinearities c.f. James 1977) and the use of control targets in the scenes that allowed us to demonstrate the linear relationship between reflectance and exposure. This meant that 3 colors density readings could be related to 3 color reflectance values for points on the earth. Image processing of color film was largely done using analog methods that were usually limited to simple two band combinations that would allow the generation of images whose brightness was proportioned to a ratio of color bands (c.f. Piech and Walker 1974).

2.2 Color Analysis Methods

The remote sensing communities use of 3 color data focused heavily on the correlation of single band or simple band ratios with material condition. For example, the amount of chlorophyll in a water column was shown to be related to the B/G reflectance ratio (c.f. Piech et al. 1978) and soil moisture could also be related to reflectance ratios (c.f. Piech and Walker 1974). Most of these methods required a number of on site measurements (what the remote sensing community calls ground truth) and were only valid in localized areas over which most other variables were constant. More importantly these methods generally relied on spatially oriented photo interpretation to provide most of the analysis with the color data used to delineate variations within a class.

3. Multispectral Remote Sensing

The limited number of degrees of freedom (3), the high band-to-band correlation and the interest in spectral signatures that might lie beyond the visible led to interest in more spectral bands covering a wider spectral range.

3.1 Multispectral Sensor and Processing Technology

The first forays into multi spectral remote sensing began with film-based tools. One of the earliest, and still among the most widely used, was the use of color infrared film. This is a 3-band film much like true color positive film. The difference is that the effective film sensitivities are in the green, red and infrared and the film is developed such that the green, red and infrared energy modulate the blue, green and red brightness values (densities) of the processed color film. The results and motivation are shown in Figure 1. The reflectance of vegetation is very high in the infrared resulting in a red appearance in the color infrared image. The film was widely used to detect early camouflage that mimicked vegetation in the visible but not in the infrared.

The image in Figure 1 shows a more modern camouflage that attempts to track the reflectance of vegetation. In general the camouflage looks like stressed vegetation (lower infrared return) and can often be detected by the color tones in the color infrared images. The agriculture and forestry communities become very intrigued with the use of near infrared imagery because much of the subtle variation in vegetation density, health and type was manifest as brightness variations in the infrared images. To look at more and narrower spectral bands, film systems were developed that used spectral filters and broadband panchromatic film (0.4 - 0.95cm) to acquire multiple black and white images representing many spectral bands. The fundamental limits on the sensitivity of film led to the evolution of electro optical imaging systems employing solid-state detectors. These systems were capable of sensing in many bands across the spectral range from 0.4μm to 14μm. Large amounts of multispectral imagery became available in 1972 when NASA's first Landsat satellite began collecting 4 spectral band images of the globe (green, red, and 2 near infrared bands). Subsequent Landsat satellites added more bands with the current Landsat 7 instrument acquiring data from the blue through the long wave infrared (10-12.5μm) in 7 bands most with approximately 30m-sample size on the ground. The Landsat data also represented the first wide spread access to digital data and ushered in the use of digital image processing as a means to analyze remotely sensed data.

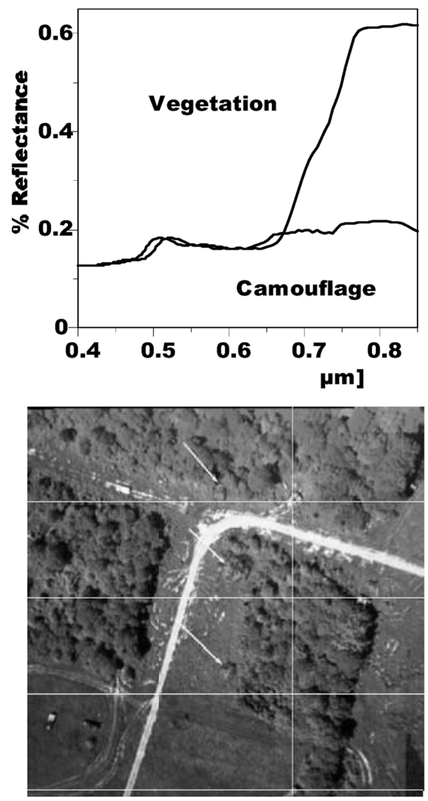


Figure 1. Illustration of the difference between early camouflage reflectance spectra and vegetation. The color infrared image illustrates how modern camouflage begins to mimic vegetation.

3.2 Multispectral Analysis Methods

Access to many bands of data coupled with the digital format of the data led to new ways of thinking about analyzing remotely sensed data. More emphasis shifted to computer based methods of analysis and mathematical representations of the data. Increasingly we tried to use the spectral variability in the data to allow us to segment the data into different material classes or land cover types. This was done by representing the data in each pixel as a spectral vector, made up of the brightness or digital count in each band. By interactively selecting regions in an image characteristic of each material type of interest we can train algorithms to learn what a material type looks like. In the simplest case the mean vector for each class can be computed and then any other pixel can be assigned to a class based on which of the class means it is closest to, using simple Euclidean distance as a measure of closeness i.e.,

$$d_i = \left[(X - M_i)^T (X - M_i)\right]^{\frac{1}{2}} \quad (1)$$

where d_i is the Euclidean distance from the pixel vector **X** to the mean vector for the i^{th} class $\mathbf{M}_i$. This method can be extended to account for the spectral variability in the data using the Gaussian Maximum Likelihood (GML) classifier. The GML classifier uses the spectral covariance of each material class computed from the training data, plus the class means, to compute which material class each pixel is most like and then assigns the pixel to that class (c.f. Schott 1997). A wide range of multispectral classifiers have evolved from these basic approaches. By taking advantage of the inherent spectral variability in natural surfaces and the higher dimensionality of the data available from modern systems (often 6 – 15 bands) a high degree of classification accuracy (85 – 95%) is achievable for a modest number of classes (6 – 15). A limitation of this approach is that the classifiers must be retrained for each image since the mean and covariance vectors are a function of illumination, atmospheric and sensor response characteristics. Two approaches have been developed to overcome this limitation. The first approach is to transform the data into engineering units (e.g. reflectance) or at least into a common set of units (e.g. the same brightness scale as a previously analyzed image). In this fashion, previously trained classifiers can be used on any new data set. The second approach uses an unsupervised classification or clustering technique to find spectrally similar pixels in a multispectral image (c.f. Duda and Hart 1973). The spectrally similar pixels are then assigned to a common class, which in many cases corresponds to a meaningful land cover class. Clearly the user must decide if the spectrally generated classes have intuitive meaning and assign class descriptions.

Once an image has been classified we are often interested in describing the condition of a class. In many cases conditions of interest can be described based on linear combinations of spectral values. For example, a commonly used indicator of vegetation vigor (health and biomass) is the Normalized Difference Vegetation Index (NDVI), which can be computed on a per pixel basis as:

$$NDVI = \frac{IR - R}{IR + R} \qquad (2)$$

where IR and R are the brightness (expressed as digital count, radiance or reflectance depending on the level of radiometric calibration available) in the near infrared and red respectively (Rouse et al. 1973). The combination of a difference and a ratio in the NDVI metric tends to mitigate illumination and atmospheric variations within and between scenes to make NDVI type metrics more consistent over many images. Figure 2 shows a NDVI image of North America assembled from many satellite images (to achieve both coverage and cloud free results). Figure 3 shows a global image map where the land areas have been processed to show NDVI and the water regions have been processed with multispectral data from a second sensor using a simple linear combination of spectral band values that is correlated with chlorophyll content in the water.

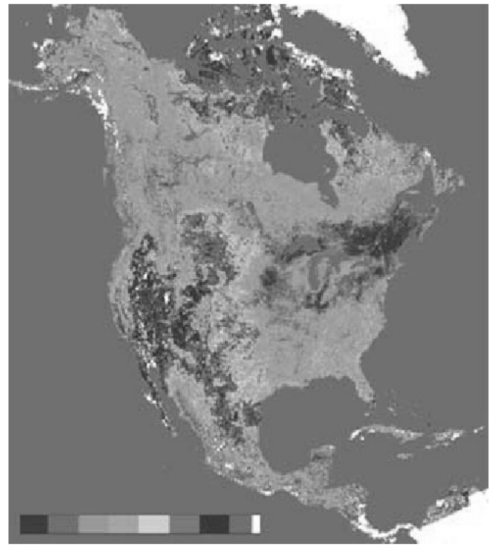


Figure 2. Map of the normalized difference vegetative index of North America derived from AVHRR data. (Image produced jointly by the Canada Center for Remote Sensing and the EROS Data Center.)

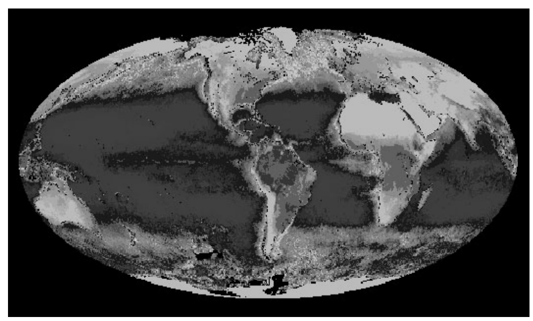


Figure 3. This image shows the vegetation vigor over land as mapped using NDVI applied to AVHRR imagery and chlorophyll content in the ocean surface waters derived from the coastal zone color scanner satellite program. (Image from Goddard Space Flight Center Earth Sciences Distributed Active Archive Center's Ocean Color)

4. Spectroscopic Remote Sensing

Multispectral remote sensing allows the classification of scenes into handfuls of classes and at least the relative characteristic of the condition within certain classes. However, it often requires a great deal of ancillary data to calibrate or correct the data for atmospheric and illumination effects and the number of land cover or material classes is often limited by spectral ambiguity between the data from a small number of bands. This has led the remote sensing community to develop imaging spectrometers capable of forming images where each pixel can be represented as a spectrogram consisting of tens to hundreds of spectral samples. The hope behind imaging spectroscopy is that these spectrograms will carry detailed information about what materials are present in a pixel and what the condition or status of the material may be.

4.1 Spectroscopic Sensor and Processing Technology

There are several spectrometer designs in use today. Much of the readily available data comes from NASA's Advanced Visible Infrared Imaging Spectrometer (AVIRIS). The AVIRIS instrument acquires data in 224 spectral band (roughly 10nm bandwidth on 10nm centers from 0.4-2.5μm [c.f. Vane et al. 1993]). The image data from what is referred to as an image cube.

Two dimensions of the cube are spatial and the third is spectral. Figure 4 shows an example image from an airborne imaging spectrometer illustrating the cube concept as well as the ability to interrogate any pixel to generate a spectrum. The AVIRIS sensor and RIT's MISI sensor that generated the image in Figure 4 are line scanners which use a mirror moving in the cross track direction to form one spatial dimension of the image and the forward motion of the aircraft to form the other spatial dimension (c.f. Figure5a). The spectral dimension is formed by one or more diffraction spectrometers dispersing the spectrum onto linear arrays of detectors. A commonly used alternative is a push broom design that uses two-dimensional arrays. One dimension is used to gather spatial data in the cross track direction and the other gathers spectral data (c.f. Figure 5b). The push broom design has been developed using both grating and prism spectrometers. Instruments have now been developed that acquire spectral data in atmospheric windows ranging anywhere from 0.4-14μm. Most of these instruments generate 50 to a few hundred spectral samples. An alternate approach uses a Fourier transform imaging spectrometer to generate hundreds or thousands of two-dimensional interferograms that can be transformed into very high resolution imaging spectrograms (i.e. image cubes) (c.f. Wadsworth et al. 1997). To date, most imaging spectrometers have been flown on airborne instruments. However, NASA is flying a simplified imaging spectrometer called MODIS (36 spectral bands) in space, which generates global data sets with approximately 1km spatial resolution (c.f. Salomonson et al. 2002). Figure 6 shows a MODIS image of the east coast generated from three of its spectral bands illustrating the wide area coverage available from space. In addition, NASA is flying a research instrument called Hyperion, which is a true imaging spectrometer with hundreds of bands and high spatial resolution (30m). However, because Hyperion is a research instrument it only generates relatively limited coverage of the earth (c.f. Pearlman et al. 2001).

The spectral nature of the data from these instruments results in very large data sets requiring much more computer power to store, transmit and analyze the image cubes. Only in the last few years have advances in communication bandwidth and processing power made use of these data practical. The combination of advances in sensor technology coupled with high speed and parallel processing have opened the door for the use of advanced processing tools, which can generate results in reasonable times.

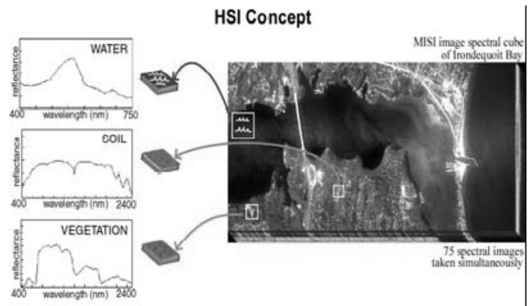


Figure 4. Illustration of the image cube concept including the concept of spectral vectors associated with each pixel. The top of the image cube shows a 3-band true color image acquired with RIT's 75 band imaging spectrometer (MISI).

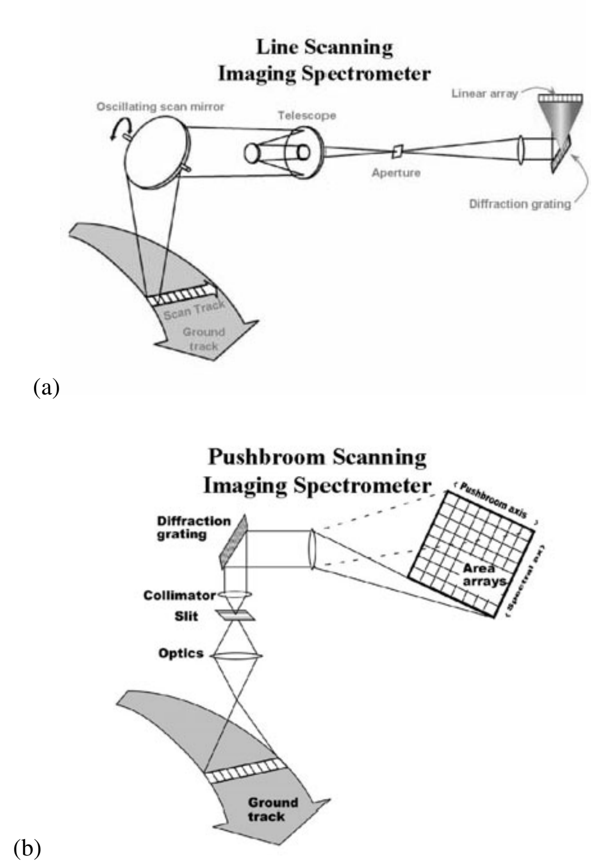


Figure 5. (a) Illustration of the line scanner and (b) push broom scanner imaging spectrometer designs.

Figure 6. MODIS Moderate Resolution Imaging Spectroradiometer. Image of the East Coast

4.2 Spectroscopic Analysis Methods

Access to imaging spectrometer or hyperspectral data has opened the door for a wide range of analysis tools focused on the spectral nature of the data. To date simultaneous processing of the spatial and spectral properties has been rather limited. In part this is because of the initial interest in taking advantage of the here-to-fore unavailable spectral properties in the data. In addition, most data available from imaging spectrometers has been of relatively low spatial resolution making it difficult to take advantage of spatial structure in analyzing the data.

One of the earliest methods of analyzing imaging spectrometer data was based on the assumption that the spectral character associated with any pixel was the result of a combination of spectral signatures due to a spatial mixture of material types within the pixel. This concept of sub pixel analysis is not driven as much by the lower spatial resolution of hyperspectral data as by the fact that the higher dimensionality of the spectroscopic data allows us to extract sub pixel information. One way to extract the sub pixel data is to use an approach called unmixing (c.f. Smith et al 1990). In its simplest form, we use a model to describe the spatial mixing of material exemplars (called end members) that combine to cause an observed spectrum. This can be expressed as:

$$\mathbf{X} = \sum_{i=1}^{n} f_i \mathbf{E}_i \tag{3}$$

where **X** is the spectral vector associated with a pixel, f_i, is the spatial fraction of the i^{th} end member represented in the pixel, $\mathbf{E}_i$ is the exemplar spectrum associated with a pure pixel of material type and is the number of materials (end members) that may be combined in the pixel. Inspection of Equation 3 shows that as long as the spectral dimension of the **X** and **E** vectors exceeds the number of end members n then we can estimate the values for the fractions (f_i) of each end member in a pixel. In practice this is usually applied in a region of interest (e.g. an agricultural field) where we can severely restrict the possible end members (e.g. corn, weeds, soil). The output of this process is an estimate of the fractional amount of each end member in each pixel. These can be used to generate fraction maps or abundance maps showing the spatial distribution of each end member coded by brightness or combinations of end member maps can be displayed using color-coding schemes.

The difficult part of implementing Equation 3 is to define the pure end member spectra. In many cases, pure spectra may not exist in a scene or they may be difficult to identify by photo interpretation. An alternative to extracting the data from the image is to use library values of spectral reflectance values acquired with laboratory of field spectrometers. The use of reflectance libraries requires us to transform the image cube data from digital counts to surface reflectance values. Typically this is a two-step process where the first step is to convert the digital count values into the sensor reaching radiance that caused that digital count level. This is the result of instrument calibration. The second step involves correcting the radiance spectrum for the effects of illumination and atmospheric propagation and results in a reflectance spectrum. This second step has plagued the analysis of color and multispectral data. In essence it has only been solved effectively for those cases where known reflectance standards existed in the image.

However, analysis of hyperspectral data showed that the magnitude of atmospheric effects could be detected by the strength of spectral absorption features recorded in the spectrum associated with each pixel (c.f. Figure 7). By comparing models and measurements of the shape and depth of absorption features (e.g. water vapor) it is possible using imaging spectrometer data to generate atmospherically corrected image cubes expressed as surface reflectance spectra (c.f. Green et al 1993 and Gao and Goetz 1990). Once the data are in reflectance space, library end members can be used in the unmixing process.

A variety of other spectral analysis techniques have been developed for analysis of hyperspectral data. Many of these involve looking for spectral similarities between a spectrum of interest and every pixel in an image (c.f. Kruse et al. 1993 and Harsanyi and Cheng 1994). Many of these methods allow detection of subpixel manifestations of the target of interest even though it may only exist as a small spatial fraction within a pixel. These techniques can be combined to map the presence and estimate the concentration of many material types within an image.

Figure 8 shows how AVIRIS data can be analyzed to generate mineral maps for geologic studies and Figure 9 illustrates how the three primary coloring agents in coastal waters can be mapped to their concentration levels based on analysis of the spectral data. While the details of these analyses methods are beyond the scope of this paper it should be clear that the high dimensionality of the spectral data offers the opportunity for much more detailed and subtle analysis of both what is present in an image and what is the concentration or condition of the material present.

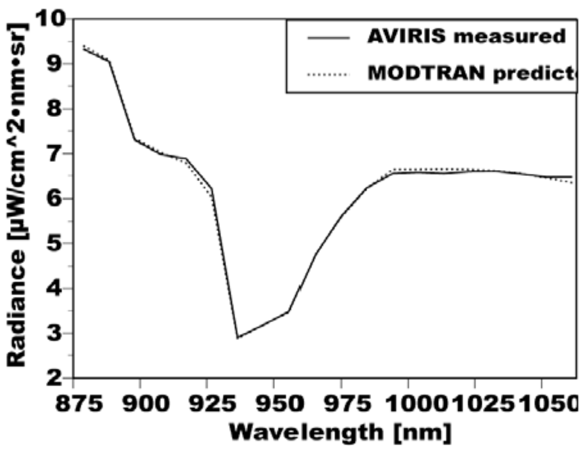


Figure 7. Comparison of measured and predicted spectral characteristics near the 940-nm water absorption band.

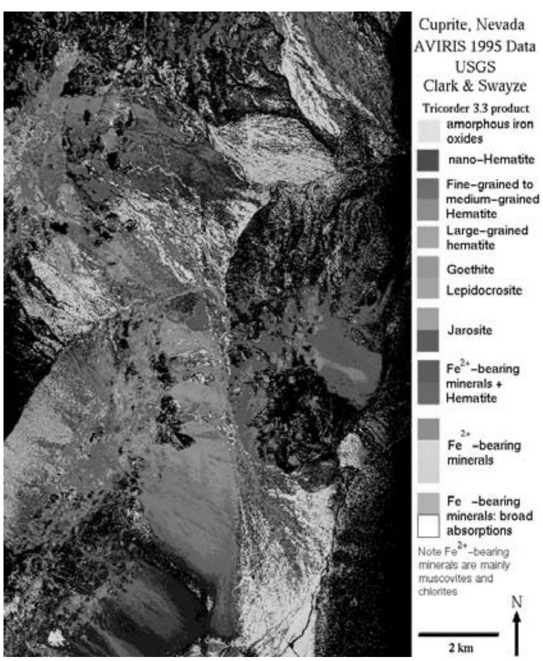


Figure 8. Detailed mineralogical map produced by analysis of imaging spectrometer data. (Image from U.S. Geological Survey Spectroscopy Lab)

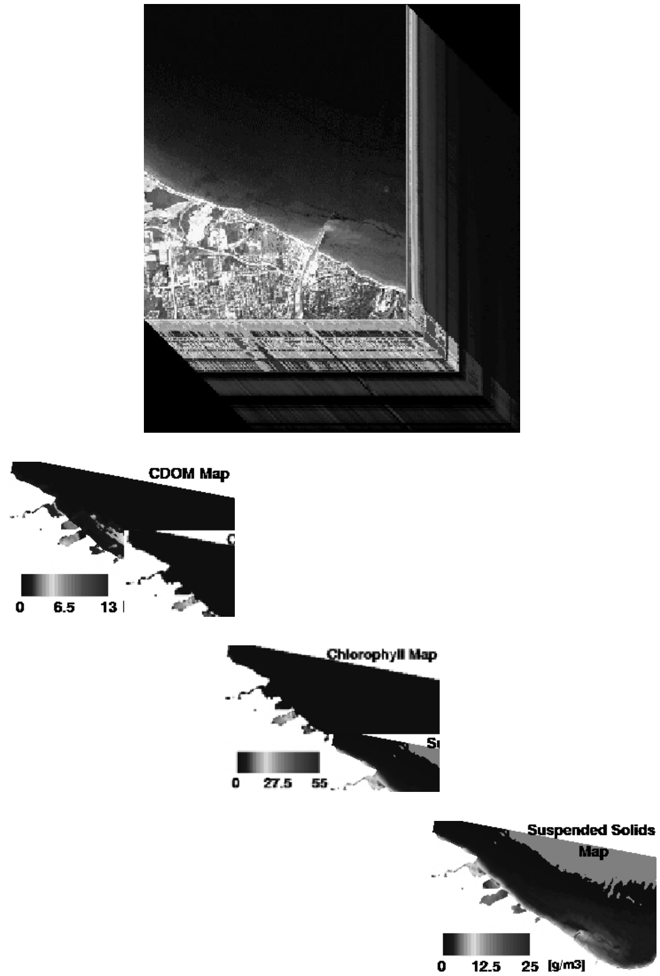
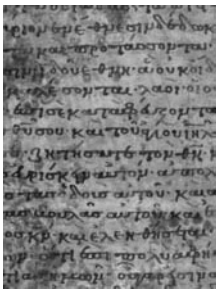


Figure 9. Zoom of an AVIRIS image cube of Lake Ontario along with concentration maps of colored dissolved organic material, CDOM, chlorophyll and suspended solids derived from spectral analysis of the AVIRIS data.

5. Extension to Other Disciplines

The remote sensing community has led the way in many aspects of spectroscopic image analysis because they were early developers and adopters of the sensing technology. However both the sensing and analysis tools are readily adapted to many other disciplines that seek to use images to understand the subject under study. In particular push broom imaging spectrometers can easily be developed for close range imaging in support of fields such as nondestructive testing, art conservation and machine vision. The access to spectral regions beyond the visible can open the doors to phenomena that can't be sensed in the visible. The higher dimensional data offers the opportunity to segment out a wider range of variables than can be addressed with color or multispectral systems. For example, identifying the presence or even the concentration of multiple dyes in an artifact of interest. Because the environment can be controlled, many of the steps used in remote sensing (e.g. atmospheric correction) can be simplified for use in other fields. In other cases, the remote sensing tools may provide insights into how to initiate extensions to other fields. For example, can the tools used to correct for atmospheric effects in remotely sensed images be used to characterize and correct for the impact of aging varnishes on the appearance of underlying paint pigments. Figure 10 shows an example of how remote sensing spectral analysis techniques have been used to help bring out the overwritten text in an ancient manuscript.



Original

Processed by Matched Filter

Processed by Least Squares

Figure 10. Illustration of how spectral image processing tools developed from remote sensing can be used to analyze spectral images of ancient documents. In the original the overwritten text is clear and the original text is almost completely obscured. The bottom two panels show how spec-processing was applied to bring out the original text and illustration. "Photograph: Produced by The Rochester Institute of Technology and Johns Hopkins University. Coed. tral pyright resides with the owner of the Original Processed by Least Squares

A major limitation of imaging spectroscopy is the assumption that more spectral bands means more information. In fact, there are many cases where the spectral information is highly correlated across wide regions of the spectrum such that more bands may add little or no new information. More importantly, the increase in the inherent dimensionality of the data (a rough estimate of the number of variables that may be separable and explainable by the spectral data) is almost never directly tied to the increase in the number of bands. Thus a remotely sensed image with 200+ bands may have an inherent dimensionality of only 10-20 dimensions and for some scenes perhaps only a few inherent dimensions. Thus the user should be cautioned about how much information to expect from imaging spectroscopy. Most importantly, the fundamental limitation of remote sensing should be kept in mind. We can only hope to sense those phenomena that have an optical manifestation. Many problems do not have optical manifestations at the spatial spectral dimensions available for remote sensing.

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