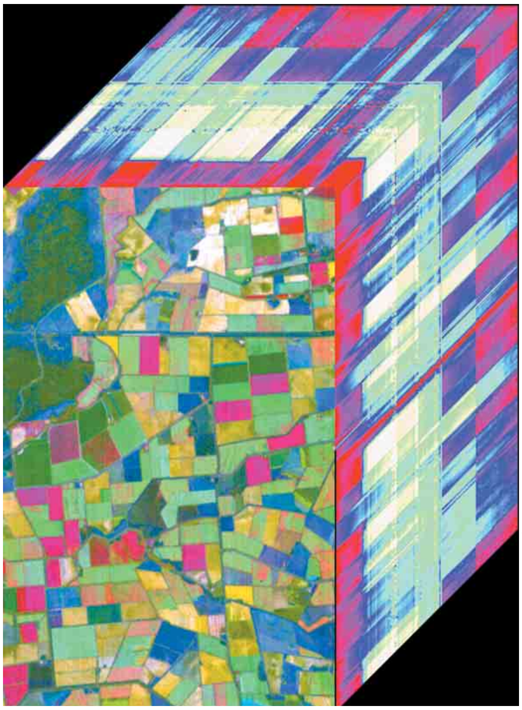
Spotlight on Hyperspectral

Peg Shippert



Courtesy of Research Systems, Inc.

Hyperspectral images are sometimes referred to as "image cubes" because of the large number of measured wavelengths. The face of the cube in this example is an image of an agricultural region in Australia, which was collected by the Hyperion sensor. The top and right side of the cube show hundreds of color-coded pixel values measured for each pixel along the top and right edge of the image.

From analyzing eelgrass beds in the Pacific Northwest to identifying pathfinder minerals for geological exploration, hyperspectral imagery and analysis is proving its worth for diverse remote sensing tasks.

Among the most significant recent breakthroughs in remote sensing has been the development of hyperspectral sensors and the software to analyze the resulting image data. A short time ago, only spectral remote sensing experts had access to hyperspectral images and the software tools necessary to take advantage of them. During the past decade, though, hyperspectral image analysis has matured into one of the most powerful and fastest-growing technologies in the field of remote sensing.

A hyperspectral image is one in which the reflectance from each pixel is measured at many narrow, contiguous wavelength intervals. Such an image provides detailed spectral signatures for every pixel. These signatures often provide enough information to identify and quantify the material(s) existing within the pixels. A user could, for instance, employ a hyperspectral image to locate and quantify different types of building materials or minerals that might be present within an area of interest or even within a single pixel.

This article will discuss the difference between hyperspectral and multispectral images, introduce relevant spectral concepts, review some recent applications of hyperspectral image analysis, and summarize image-processing techniques commonly applied to hyperspectral imagery.

Spectral image basics

To understand the advantages of hyperspectral imagery, it helps to first review some basic spectral remote sensing concepts. You may recall that each photon of light has a wavelength determined by its energy level. Light and other forms of electromagnetic radiation are commonly described in terms of their wavelengths. For example, visible light has wavelengths between 0.4 and 0.7 microns, whereas radio waves have wavelengths greater than about 1 millimeter (see Figure 1).

Reflectance is the percentage of light hitting a material that is then reflected by that material (as opposed to being absorbed or transmitted). A reflectance spectrum shows the reflectance of a material measured across a range of wavelengths. Some materials will reflect certain wavelengths of light, while other materials will absorb the same wavelengths. Many materials have unique

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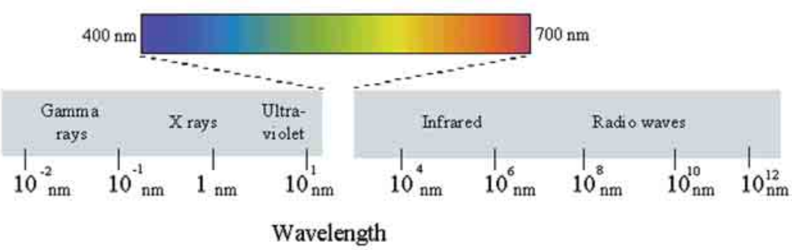


FIGURE 1 The electromagnetic spectrum with the region of visible light expanded.

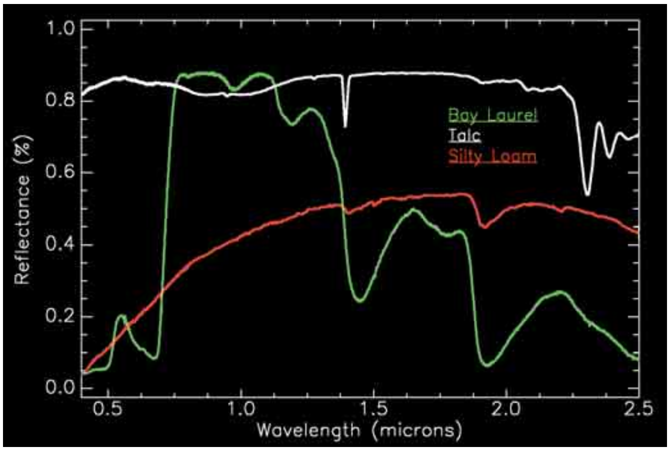


FIGURE 2 Here we see the reflectance spectra measured by laboratory spectrometers for three materials — a green bay laurel, mineral talc, and silty loam soil.

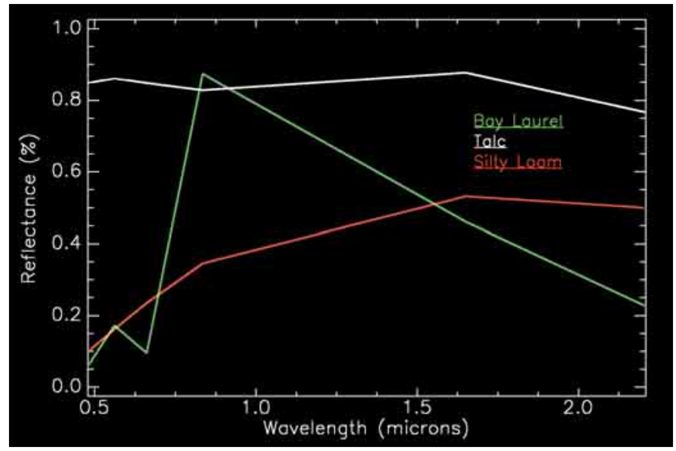


FIGURE 4 In this figure, we see the reflectance spectra of the same three materials seen in Figure 2 as they would appear to the multispectral Landsat 7 sensor.

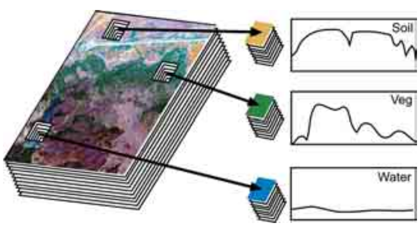


FIGURE 3 In hyperspectral imagery, measurements are made at many narrow, contiguous wavelength bands, resulting in a complete spectrum for each pixel.

patterns of reflectance and absorption across wavelengths. The reflectance spectra in Figure 2, for instance, reveal three different materials. Many materials can be identified by their spectra.

Field and laboratory spectrometers usually measure reflectance at many narrow, closely spaced wavelength bands, so that the resulting spectra appear to be continuous curves as seen in Figure 2. When a spectrometer is used in an imaging sensor, the resulting images record a reflectance spectrum for each pixel in the image (see Figure 3).

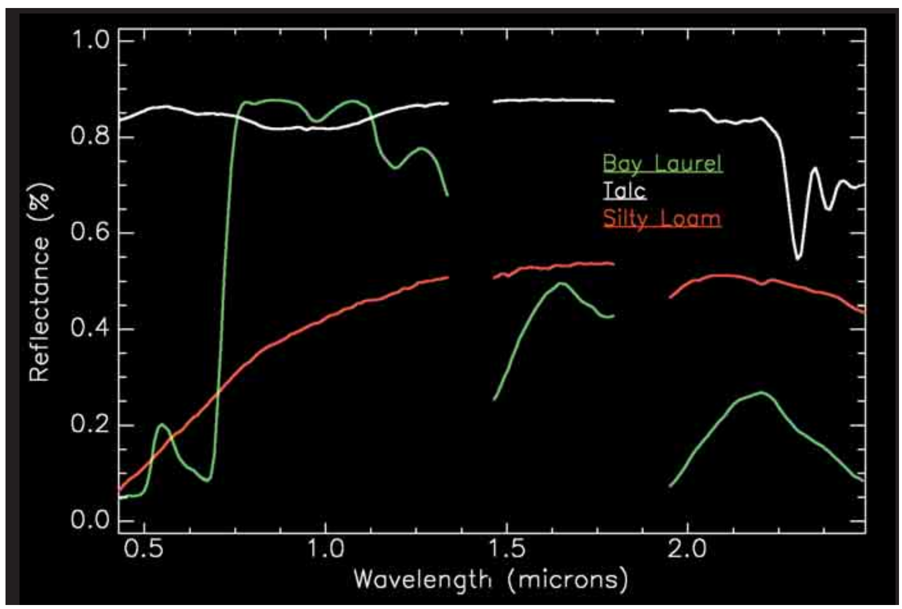


FIGURE 5 This example reveals the reflectance spectra of the same three materials shown in Figures 2 and 4 as they would appear to the hyperspectral Airborne Visible Infrared Imaging Spectrometer, or AVIRIS. The gaps in the spectrum are wavelength ranges at which the atmosphere absorbs so much light that no reliable signal is received from the surface.

Hyperspectral sensors

Remote sensing has included multispectral sensors — sensors which collect images for a small number of broad wavelength bands — since Landsat 1 was launched in 1972. Although multispectral sensors were revolutionary when first introduced, they lack sufficient spectral resolution for precise surface studies because of their low number of spectral bands(see Figure 4). In contrast to multispectral instruments, hyperspectral sensors measure hundreds of narrow, contiguous wavelength bands. In fact, the hyper in hyperspectral means "over," or "too many." So you might say that hyperspectral images measure too many wavelengths. When we look at a spectrum for one pixel in a hyperspectral image it looks very much like a detailed spectrum that would be measured in a spectroscopy laboratory (see Figure 5). This type of detailed pixel spectrum provides much more information about the surface than a multispectral pixel spectrum. Thus, hyperspectral imagery provides the potential for more accurate and detailed extraction of information than is possible with multispectral remote sensing technology.

Although most hyperspectral sensors measure hundreds of wavelengths, it is not the number of measured wavelengths that defines a sensor as hyperspectral. Rather it is the narrowness and contiguous nature of the measurements. For example, a sensor that measures only 20 bands would be considered hyperspectral if those bands were contiguous and, say, 10 nanometers wide. If the sensor measures 20 wavelength bands that are 100 nanometers wide, or that are separated by nonmeasured wavelength ranges, the sensor would not be considered hyperspectral.

A passive system. Most hyperspectral imaging sensors, like most multispectral imaging sensors, are passive optical sensors. This means that they measure the amount of visible and infrared radiance passively reflected or emitted from the surface. Passive optical sensors operating in visible and near- infrared wavelengths detect sunlight energy reflected by surfaces while the sun is illuminating the Earth. There is no reflected energy available from the sun in these wavelength regions at night, so images cannot be collected at night. Energy that is naturally emitted (such as thermal infrared), however, can be detected day or night. All hyperspectral sensors are spectrometers, which means that they include a prism or diffraction grating that can break the incoming radiation into discrete wavelengths, which are then dispersed separately to detectors. Thus, hyperspectral sensors are often referred to as imaging spectrometers.

The signal measured by an airborne hyperspectral sensor is generally digitized and then recorded onboard the aircraft, and retrieved once the aircraft lands. The signal measured by a satellite hyperspectral sensor is digitized and then electronically transmitted to a ground receiving station. Most hyperspectral data providers will convert hyperspectral image data to radiance units before distributing the data. Although hyperspectral images are usually not georeferenced, some data providers will georeference hyperspectral images to a map projection or latitude/longitude grid on request. Some data providers offer location information that the end user can employ to georeference the data. Radiometric and geometric accuracy of the data, as well as pixel size and image swath width, vary significantly among hyperspectral sensors. It is recommended that users of hyperspectral data explore these issues with their data provider prior to purchasing data.

Platforms. For the most part hyperspectral sensors have been airborne (see Table 1) with two recent exceptions: NASA's Hyperion sensor on the EO-1 satellite and the U.S. Air Force Research Lab's FTHSI sensor on the MightySat II satellite. Several new space-based hyperspectral sensors, though, have recently been proposed (see Table 2 on page 44). Unlike airborne sensors, space-based sensors can provide near global coverage repeated at regular intervals. Therefore, the amount of hyperspectral imagery available should increase significantly in the near future as new satellite-based sensors are successfully launched.

Image analysis broadbrush

Hyperspectral imagery has been used to detect and map a wide variety of materials having characteristic reflectance spectra. For example, hyperspectral images have been used by geologists for mineral mapping (Clark et al., 1992; 1995) and to detect soil properties including moisture, organic content, and salinity (Ben-Dor, 2000). Vegetation scientists have successfully used hyperspectral imagery to identify vegetation species (Clark et al., 1995), study plant

TABLE 1 Current hyperspectral sensors

Satellite sensors	Manufacturer	Number of bands	Spectral range (in microns)
FTHSI on MightySat II	Air Force Research Lab www.vs.afrl.af.mil/ TechProgs/MightySatII	256	0.35–1.05
Hyperion on EO-1	NASA Goddard Space Flight Center eo1.gsfc.nasa.gov	220	0.4–2.5
Airborne sensors	**Manufacturer**	**Number of bands**	**Spectral range (in microns)**
AVIRIS (Airborne Visible Infrared Imaging Spectrometer)	NASA Jet Propulsion Lab makalu.jpl.nasa.gov/	224	0.4–2.5
HYDICE (Hyperspectral Digital Imagery Collection Experiment)	Naval Research Lab	210	0.4–2.5
PROBE-1	Earth Search Sciences Inc. www.earthsearch.com	128	0.4–2.5
casi (Compact Airborne Spectrographic Imager)	ITRES Research Limited www.itres.com	up to 228	0.4–1.0
HyMap	Integrated Spectronics www.intspec.com	100 to 200	Visible to thermal infrared
EPS-H (Environmental Protection System)	GER Corporation www.ger.com	VIS/NIR (76), SWIR1 (32), SWIR2 (32), TIR (12)	VIS/NIR (.43–1.05), SWIR1 (1.5–1.8), SWIR2 (2.0–2.5), and TIR (8–12.5)
DAIS 7915 (Digital Airborne Imaging Spectrometer)	GER Corporation	VIS/NIR (32), SWIR1 (8), SWIR2 (32), MIR (1), TIR (6)	VIS/NIR (0.43–1.05), SWIR1 (1.5–1.8), SWIR2 (2.0–2.5), MIR (3.0–5.0), and TIR (8.7–12.3)
DAIS 21115 (Digital Airborne Imaging Spectrometer)	GER Corporation	VIS/NIR (76), SWIR1 (64), SWIR2 (64), MIR (1), TIR (6)	VIS/NIR (0.40–1.0), SWIR1 (1.0–1.8), SWIR2 (2.0–2.5), MIR (3.0–5.0), and TIR (8.0–12.0)
AISA (Airborne Imaging Spectrometer)	Spectral Imaging www.specim.fi	up to 288	0.43–1.0

Footnotes: VIS = visible NIR = near infrared SWIR = shortwave infrared TIR = thermal infrared MIR = mid infrared canopy chemistry (Aber and Martin, 1995), and detect vegetation stress (Merton, 1999). Military personnel have used hyperspectral imagery to detect military vehicles under partial vegetation canopy and to achieve many other military target detection objectives. The type of quantitative information extraction in the studies mentioned above usually requires accurate preprocessing of the hyperspectral imagery and collection of accurate auxiliary data. Among the first challenges faced when performing quantitative analysis of hyperspectral data, for instance, are those encountered due to the atmosphere.

Atmospheric correction. When sunlight travels from the Sun to the Earth's surface and then is reflected to an air- or spaceborne sensor, the intervening atmosphere often scatters some light. Therefore, the light received at the sensor may be more or less than that caused by reflectance from the surface alone. Atmospheric correction attempts to minimize these effects on image spectra and is an indispensable step before conducting quantitative image analysis or change detection using multispectral or hyperspectral data. Sophisticated atmospheric correction algorithms are available to calculate concentrations of atmospheric gases directly from the detailed spectral information contained in hyperspectral imagery, without additional data about atmospheric conditions.

Spectral libraries. Another often critical element for spectral analysis is a good spectral library. Spectral libraries are collections of reflectance spectra measured from materials of known composition, usually in the field or laboratory. Comparing hyperspectral data with data in a spectral library can help a user to quickly identify the material in question. Spectra from libraries can also guide spectral image classifications or define targets to use in spectral image analysis. Many investigators collect spectral libraries for materials in their field sites as part of every project to facilitate analysis of multispectral or hyperspectral imagery from those sites. Several high-quality spectral libraries are also publicly available (for instance, Clark et al., 1993; Grove et al., 1992; Elvidge, 1990; Korb et al., 1996; Salisbury et al., 1991a; Salisbury et al., 1991b; Salisbury et al., 1994).

TABLE 2 Proposed space-based hyperspectral sensors

Satellite	Sensor	Agencies
ARIES-I (Australian Resource Information and Environment Satellite)	ARIES-I	Auspace Ltd ACRES Geoimage Pty. Ltd. CSIRO Earth Resource Mapping Pty. Ltd.
PROBA (Project for On Board Autonomy)	CHRIS	European Space Agency
NEMO (Naval EarthMap Observer)	COIS	Space Technology Development Corp. Naval Research Laboratory
PRISM (Process Research by an Imaging Space Mission)	PRISM	European Space Agency

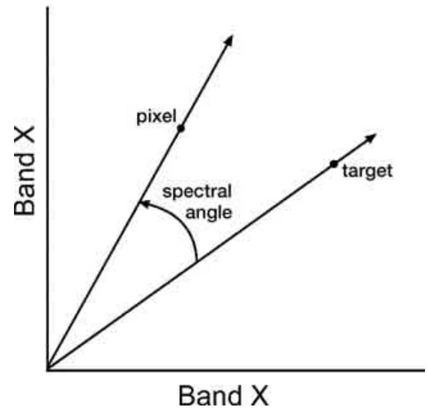


FIGURE 6 Pixel and target spectra plot as points in this scatter plot of pixel values. If a vector is drawn from the origin through each point, the angle between any two vectors constitutes the spectral angle between those two points.

Analysis methodology

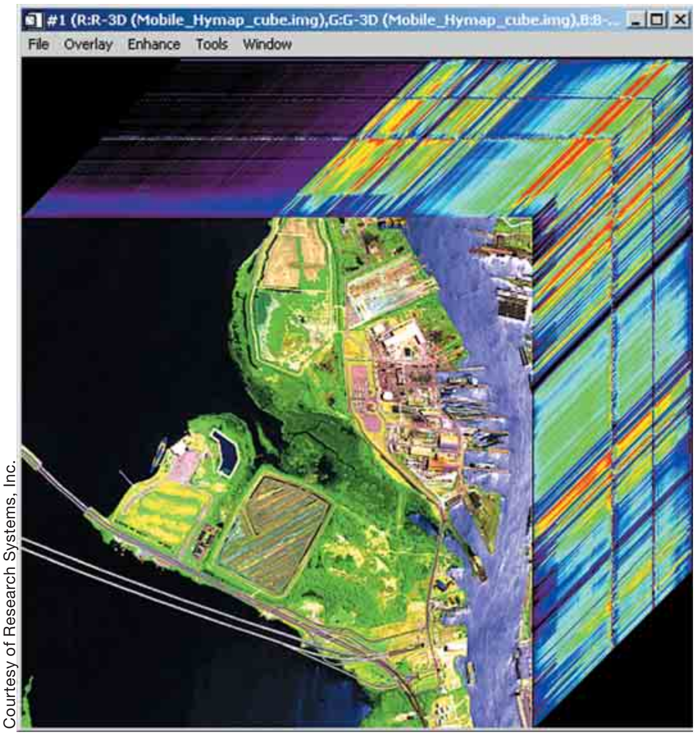
Many image analysis algorithms have been developed specifically to exploit the extensive information contained in hyperspectral imagery. Most of these algorithms also provide accurate, although more limited, analyses of multispectral data. Spectral analysis methods usually compare pixel spectra with a reference spectrum (often called a target). Target spectra can be derived from a variety of sources, including spectral libraries, regions of interest within a spectral image, or individual pixels. Now let's discuss some relatively common hyperspectral/multispectral image analysis methods.

Whole-pixel. Whole-pixel analysis methods attempt to determine whether one or more target materials are abundant within each pixel in a multispectral or hyperspectral image on the basis of the spectral similarity between the pixel and target spectra. Whole-pixel scale tools include standard supervised classifiers such as minimum distance or maximum likelihood (Richards and Jia, 1999), as well as tools developed specifically for hyperspectral imagery such as spectral angle mapper (SAM) and spectral feature fitting.

SAM. Consider a scatter plot of pixel values from two bands of a spectral image. In such a plot, pixel spectra and target spectra will plot as points (see Figure 6). If a vector is drawn from the origin through each point, the angle between any two vectors constitutes the spectral angle between those two points. The SAM (Yuhas et al., 1992) computes a spectral angle between each pixel spectrum and each target spectrum. The smaller the spectral angle, the more similar the pixel and target spectra. This spectral angle will be relatively insensitive to changes in pixel illumination because increasing or decreasing illumination doesn't change the direction of the vector, only its magnitude (a darker pixel, for instance, will plot along the same vector, but closer to the origin). Note that although this discussion describes the calculated spectral angle using a two-dimensional scatter plot, the actual spectral angle calculation is based on all of the bands in the image. In the case of a hyperspectral image, a spectral "hyper-angle" is calculated between each pixel and each target.

Spectral feature fitting. Another approach to matching target and pixel spectra is to examine specific absorption features in the spectra (Clark et al., 1991). An advanced example of this method, called Tetracorder, has been developed by the U.S. Geological Survey (Clark et al., 2000). A relatively simple form of this method, called spectral feature fitting, is also available in a commercial image processing software product. In spectral feature fitting, the user specifies a range of wavelengths within which a unique absorption feature exists for the chosen target. The pixel spectra are then compared with the target spectrum using two measurements. First, the depth of the feature in the pixel is compared with the depth of the feature in the target. Next, the shape of the feature in the pixel is compared with the shape of the feature in the target (often using a least-squares technique).

Subpixel methods. Subpixel analysis methods can be used to calculate the quantity of target materials in each pixel of an image. The technique 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, subpixel analysis has detected targets covering as little as 1–3 percent of the pixel. Subpixel analysis methods include complete linear spectral unmixing and matched filtering.



Courtesy of Research Systems, Inc.

The face of this image cube shows the city of Mobile, Alabama with data collected by the Hymap sensor. Again, the top and right side show color-coded pixel values measured for each pixel along the top and right edge.

Unmixing. The set of spectrally unique surface materials existing within a scene are often referred to as the spectral endmembers for that scene. Linear spectral unmixing (Adams et al., 1986; Boardman, 1989) exploits the theory that the reflectance spectrum of any pixel is the result of linear combinations of the spectra of all endmembers inside that pixel. A linear combination in this context can be thought of as a weighted average, where each endmember's weight is directly proportional to the area of the pixel containing that endmember. If the spectra of all endmembers in the scene are known, then their abundances within each pixel can be calculated from each pixel's spectrum.

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 have more equations than unknowns, it is necessary to have 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 percent of the area of the pixel contains quartz. An error image is also usually calculated to help evaluate the success of the unmixing analysis.

Matched filtering. Matched filtering (Boardman et al., 1995) is a type of unmixing in which only user-chosen targets are mapped. Unlike complete unmixing, one doesn't need to find the spectra of all endmembers in the scene to get an accurate analysis (hence, this type of analysis is often called 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 filter results.

This technique 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 zero or less would be interpreted as background (none of the target is present).

One potential problem with matched filtering is that it is possible to end up with false positive results. A solution is to calculate an additional measure called infeasibility. This measure is based on both noise and image statistics and indicates the degree to which the matched filter 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.

Final frame

Hyperspectral sensors and analyses have provided more information from remotely sensed imagery than ever possible before. As new sensors provide more hyperspectral imagery and new image processing algorithms continue to be developed, hyperspectral imagery is positioned to become one of the most common research, exploration, and monitoring technologies used in a wide variety of fields.

References

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