Hyperspectral Remote Sensing

- Multi-spectral: Several comparatively wide spectral bands
- Hyperspectral: Many (could be hundreds) very narrow spectral bands
AVIRIS: Airborne Visible/Infrared Imaging Spectrometer

• 224 continuous spectral Bands
• 400-2500 nm
• Bandwidth < 10 nm
• Main objective is to identify, measure, and monitor constituents of the Earth's surface and atmosphere based on molecular absorption and particle scattering signatures.
Hyperion

- 220 spectral channels
- 357–2576 nm
- 10 nm bandwidth
- 30-m resolution
- 7.75 km swath
- Flies on EO-1
- 12-bit dynamic range
- Launched Nov. 20, 2000

Next Generation: Hyperspectral InfraRed Imager (HyspIRI)
https://hyspiri.jpl.nasa.gov
Hyperspectral Remote Sensing

- Does not lend itself to conventional image viewing techniques with RGB color composites
  - Reducing >200 bands into three does not take advantage of the full spectrum of data

Fig. 13.2. Line profile display created from hyperspectral data. a Transect through portion of a hyperspectral image. b Greyscale display of spectral band (horizontally) versus position in the image (vertically). c Coloured version of b
Radiance vs. Reflectance

This is the average of 25 image spectra measured by the AVIRIS sensor over a bright dry lake bed surface in the Cuprite, Nevada scene.

The spectral reflectance curve for the sample area is actually relatively flat and featureless.

The spectral reflectance of the surface materials is only one of the factors affecting these measured values.
Radiance vs. Reflectance

- Detected radiance in hyperspectral remote sensing is particularly affected by:
  - Solar emittance characteristics as a function of wavelength
  - Atmospheric constituents and absorption bands
  - Reflectance spectrum of surface 0
Calibration of Hyperspectral Data

- Three main considerations taken into account before translation of radiance values into surface reflectances
  - Compensation for shape of solar spectrum to determine apparent reflectivity
    - Well-constrained by models
  - Compensation for atmospheric gas transmittance and absorption bands within the atmosphere to determine scaled reflectivity
    - Atmospheric radiative transfer models
  - Consideration of topographic effects
    - Digital elevation models
Hyperspectral Remote Sensing

• Challenges in using hyperspectral data
  – Data volume
    • Multi-spectral: 7-bands, 8-bit digitization → 56 elements
    • Hyperspectral 220 bands, 12 bit digitization → 2640
  – Data redundancy
    • Often there is little difference among neighboring spectral bands
    • The challenge is finding those with unique information
    • Redundant bands can be identified using the correlation matrix

The correlation matrix of \( n \) random variables \( X_1, ..., X_n \) is the \( n \times n \) matrix whose \( i,j \) entry is the correlation between \( (X_i), (X_j) \).

\[
R_{i,j} = \frac{CV_{i,j}}{\sqrt{CV_{i,i}CV_{j,j}}}
\]
Fig. 10.15 Correlation matrix for 196 bands of the Jasper Ridge AVIRIS image in which white represents high correlation and black represents zero correlation. Overlapping bands, bands corresponding to significant water absorption, and bands with very small means have been deleted from the original 224 band set.
Spectral Angle Mapper based Classification

• In N dimensional multispectral space a pixel vector $x$ has both magnitude (length) and an angle measured with respect to the axes that define the coordinate system of the space.

• For hyperspectral space, sometimes there are too many dimensions and the classifications break down

$$\alpha = \cos^{-1} \left( \frac{x \cdot r}{\|x\| \cdot \|r\|} \right)$$
Spectral Angle Mapper based Classification

- The spectral angle mapping approach considers only the angular information, reducing the dimensionality of the problem by not considering the magnitude
- Spectra are characterized by their angles from the horizontal axes
  - Decision boundaries are set up from library information or training data defining sectors for different classes
  - Spectra are labeled according to the sector in which they fall
  - Requires that angles are sufficiently different from one another in order to define classes

\[ \text{Fig. 13.8. a Representing pixels by their angles from the band axes. b Segmenting the multi-spectral space by angle} \]
Library Searching and SAM

- SAM is applied in multidimensional space to compare image pixel spectrum and a library reference spectrum
  - the multidimensional vectors are defined for each spectrum and the angle between the two vectors is calculated.
  - Smaller angles represent closer matches to the reference spectrum.
  - a “match” angular threshold is applied to determine whether or not a pixel falls in a particular angular class

- SAM represses the influence of shading effects to accentuate the target reflectance characteristics (De Carvalho et al., 2000)

- SAM is invariant to unknown multiplicative scalings, and consequently, is invariant to unknown deviations that may arise from different illumination and angle orientation (Keshava, et al., 2002).
Expert Spectral Knowledge and Library Searching

- Takes advantage of the presences of diagnostically significant features
  - Absorption features that provide the information needed for identification
  - Requires sufficient spectral resolution for the distinction
    - Not just identifying the dips in the reflectance but also identifying the shapes of the dips
      - Magnitude
      - Width: full-width at half maximum depth (FWHM)
Spectral mixture

• **Mixed pixel:** The signal detected by a sensor into a single pixel is frequently a combination of numerous disparate signals.

• Mixed pixels are frequent in remotely sensed hyperspectral images due to insufficient *spatial resolution* of the imaging spectrometer, or due to *intimate mixing effects*.

• The rich spectral resolution available can be used to unmix hyperspectral pixels.
Mixed pixel

• The mixture problem can happen in *macroscopic* fashion, this means that a few macroscopic components and their associated abundances should be derived.

• However, intimate mixtures happen at microscopic scales, thus complicating the analysis with nonlinear mixing effects.

**Macroscopic mixture:**
15% soil, 25% tree, 60% grass in a 3x3 meter-pixel

**Intimate mixture:**
Minerals intimately mixed in a 1-meter pixel
Linear Spectral unmixing

In linear spectral unmixing, the goal is to find a set of macroscopically pure spectral components (called endmembers) that can be used to unmix all other pixels in the data.

- Unmixing amounts at finding the fractional coverage (abundance) of each endmember in each pixel of the scene, which can be approached as a geometrical problem:

\[ f(x, y) = M\alpha(x, y) + n(x, y) \]

\[ s = \sum_{i=1}^{3} c_i \cdot e_i + \epsilon \]
Physical constraints:
• Abundances are non negative (non negativity constraint)
• Abundances sum to one for each pixel (sum to one constraint)

$$f(x,y) = M\alpha(x,y) + n(x,y)$$

$$s = \sum_{i=1}^{3} c_i \cdot e_i + \epsilon$$
Spectral Unmixing

• $M = \text{the number of endmembers}$
• $N = \text{the number of spectral bands}$
• $f_m = \text{the fraction of coverage for a particular class } m \text{ where } m \text{ is from 1 to } M$
• $R_n$ is the observed reflectance in the nth spectral band where $n$ is from 1 to $N$
• $a_{n,m}$ is the spectral reflectance of the $n^{th}$ band of the $m^{th}$ endmember

\[ R_n = \sum_{m=1}^{M} f_m a_{n,m} + \xi_n \quad n = 1, \ldots, N \]

Where $\xi_n$ is an error in band $n$

Observed reflectance in each band is the linear sum of the reflectances of the endmembers (within the uncertainty expressed in the error term)
Spectral Unmixing

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\[ R_n = \sum_{m=1}^{M} f_m a_{n,m} + \xi_n \quad n = 1, \ldots, N \]

In Matrix form: \[ R = Af + \xi \]

Where \( f \) is a column vector of size \( M \), \( R \) and \( \xi \) are column vectors of size \( N \), and \( A \) is an \( N \times M \) matrix of endmember spectral signatures by column.

Reflectance of a pixel at each wavelength

\[
\begin{bmatrix}
R_1 \\
\vdots \\
R_n \\
\end{bmatrix} =
\begin{bmatrix}
a_{1,1} & \cdots & a_{1,m} \\
\vdots & \ddots & \vdots \\
a_{n,1} & \cdots & a_{n,m} \\
\end{bmatrix}
\begin{bmatrix}
f_1 \\
\vdots \\
f_m \\
\end{bmatrix} +
\begin{bmatrix}
\xi_1 \\
\vdots \\
\xi_n \\
\end{bmatrix}
\]

Fraction of pixel occupied by each class 1 - M

Error matrix

Spectral signature of class 1

Spectral signature of class m
Spectral Unmixing

For the unmixing Matrix: \( R = Af + \xi \)

We try to find values of \( f \) that minimize \( \xi \)

If we assume we have the correct set of endmembers, the equation simplifies to

\[ R = Af \]

We solve through an error minimization using psuedo inverse (Moore-Penrose)

\[ f = (A^tA)^{-1}A^tR \]

For more explanation on this minimization refer to:
http://ltcconline.net/greenl/courses/203/MatrixOnVectors/leastSquares.htm

For information on matrix inversions refer to:
https://ardoris.wordpress.com/2008/07/18/general-formula-for-the-inverse-of-a-3x3-matrix/

Solution requires:

a) the sum of the \( f_m \) values is 1 and
b) \( 0 \leq f_m \leq 1 \) for all \( m \)
Summary: Spectral Unmixing

- Mixed pixels: A pixel that contains multiple classes
- Often we wish to distinguish sub-pixel information
- Examples:
  - Ice and water in a MODIS pixel or Passive microwave pixel
  - Mineral identification
  - Sparsely-vegetated areas
  - Densely vegetated areas
- Mixed pixel problem not well addressed with multispectral data because distinctions with limited band numbers were clear to differentiate classes
- With hyperspectral data, enough of a distinction can be made for many surface classes
- Unmixing has particular relevance for something like mineral mapping where abundance of minerals is desired parameter
- Seeks to determine the linear combination of endmembers that produce the spectral response of the pixel
  - Endmembers: pure cover types that are found in an image