HYPERSPECTRAL REMOTE SENSING

M. Sc. 2nd Semester, Paper: RSG 202.2

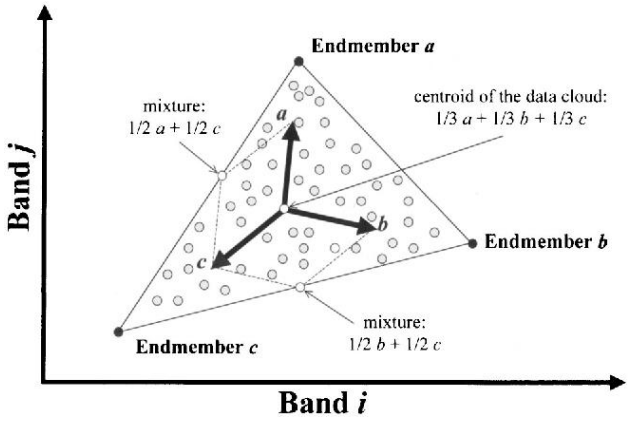
A. Endmember Collection Techniques:

1. Minimum Noise Fraction (MNF) Transform

MNF transform chooses the new components to maximize the signal to noise ratio (SNR) and orders them according to increasing image quality or decreasing noise. Minimum noise fraction (MNF) computes the noise statistics information for effectively removing the noise from the dataset and for determining the inherent dimensionality of the dataset. MNF can be treated as two cascaded Principal Component Transformations; the first is the transformation of the noise covariance matrix to an identity matrix also called as the noise whitening step. The second is the standard principal component transformation of the noise whitened dataset maximizing the signal to noise ratio (SNR) and thus segregating the signal from the noise. The noise statistics are calculated using the shift difference method also known as nearest neighbor difference.

MNF splits and projects the input image into two subspaces based on visual analysis of the images and associated eigenvalues: The first one is the Signal Subspace (signal plus noise) corresponding the largest eigenvalues and the second is the noise subspace corresponding to the lower eigenvalues. MNF images (eigen images) are used to evaluate the dimensionality of the data. Eigenvalues for bands that contain information will be an order of magnitude larger than those that contain only noise. The corresponding images will be spatially coherent, while the noise images will not contain any spatial information.

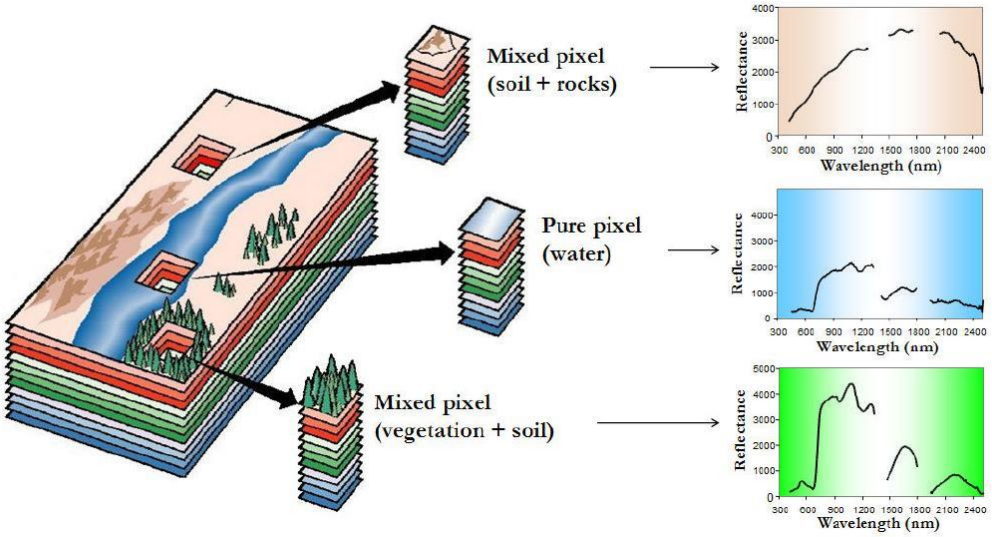
In ENVI, MNF transform is used to remove noise from data by performing a forward MNF transform. ENVI assumes that each pixel contains both signal and noise, and that adjacent pixels contain the same signal but different noise. The best noise estimate is gathered using the shift-difference statistics from a homogeneous area rather than from the whole image.



2. Pixel Purity Index

Pixel purity index (PPI) algorithm, is one of the most widely endmember extraction algorithm used for hyperspectral image analysis. PPI is a means of finding the most "spectrally pure," or extreme, pixels in the hyperspectral images. First the dataset is transformed onto lower dimensions by using either PCA or MNF as the assumption here is that the endmembers lie in the first few principal components. The endmember pixels are obtained by repeatedly projecting the transformed data onto randomly projected vectors (k) in n-dimensional space. As the vectors are randomly generated the results depend upon the number of random projections. Pixels lying at the extremes of a random vector are assigned a purity value. The values are updated after each projection and the pixels having values more than a set threshold (t) are considered as "pure" pixels. The extreme pixels in each projection are recorded and the total number of times each pixel is marked as extreme is noted. A Pixel Purity Index (PPI) image is created in which the DN of each pixel corresponds to the number of times that pixel was recorded as extreme. ENVI employs a FAST PPI method that keeps the image data into memory and performs the computations in memory, which is much faster than the disk-based PPI.

The threshold is a measure for the extremeness of the pixels. For example, a threshold of 2 marks all pixels greater than two digital numbers (DN) from the extreme pixels (both high and low) as being extreme. This threshold selects the pixels on the ends of the projected vector. The threshold should be approximately 2-3 times the noise level in the data.



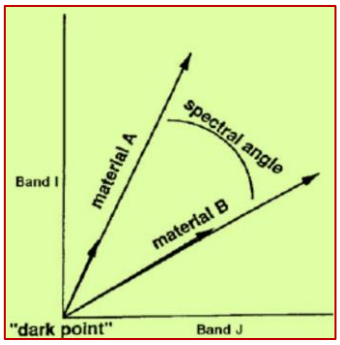
3. N-D Visualizer

Spectra can be thought of as points in an n-dimensional scatter plot, where n is the number of bands. The coordinates of the points in n-space consist of "n" values that are simply the spectral radiance or reflectance values in each band for a given pixel. The distribution of these points in n-space can be used to estimate the number of spectral endmembers and their pure spectral signatures. ENVI's n-Dimensional Visualizer provides an interactive tool for selecting the endmembers in n-space.

B. Hyperspectral Image Classification Techniques

1. Spectral Angle Mapper

SAM is a spectral classifier that is able to determine the spectral similarity between image spectra and reference spectra by calculating the angle between the spectra, treating them as vectors in a space with dimensionality equal to the number of bands used each time. Reference spectra for implementation of the technique can be taken either from laboratory or field measurements or can equally be extracted directly from the satellite imagery. 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.



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.

In a n-dimensional multispectral space a pixel vector has both magnitude (length) and an angle measured with respect to the axes that defines the coordinate system of the space. In SAM, only the angular information is used for identifying pixel spectra, as the method is based on the assumption that an observed reflectance spectrum is a vector in a multidimensional space, where the number of dimensions equals the number of spectral bands. Small angles between the two spectrums indicate high similarity and high angles indicate low similarity, whereas pixels with an angle larger than the tolerance level the specified maximum angle threshold are not classified. The thresholding value is expressing essentially the maximum acceptable angle for the separation between the end-member spectrum vector and the pixel vector in the number of bands of dimensional space. Pixels with values higher than this threshold value are not classified.

The SAM algorithm implemented in ENVI takes as input a number of training classes, or reference spectra from ASCII files, ROIs, or spectral libraries. It calculates the angular distance between each spectrum in the image and the reference spectra or endmembers in n-dimensions. The result is a classification image showing the best SAM match at each pixel and a rule image for each endmember showing the actual angular distance in radians between each spectrum in the

image and the reference spectrum. Darker pixels in the rule images represent smaller spectral angles spectra that are more similar to the reference spectrum. The rule images can be used for

$$\alpha = \cos^{-1}\left(\frac{\vec{t} \bullet \vec{r}}{\left\|\vec{t}\right\| \bullet \left\|\vec{r}\right\|}\right)$$

which also can be written as:

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

where *nb* equals the number of bands in the image.

subsequent classifications using different thresholds to decide which pixels are included in the SAM classification image.

2. Linear Spectral Unmixing

Natural surfaces are rarely composed of a single uniform material. Spectral mixing occurs when two of more materials with spectrally distinct qualities are represented by a single image pixel. If the scale of mixing is large (macroscopic), mixing occurs in a linear fashion. For microscopic or intimate mixtures, the mixing is generally nonlinear. The linear model assumes no interaction between materials. If each photon only "sees" one material, these signals add (a linear process). Multiple scattering involving several materials can be thought of as cascaded multiplications (a non-linear process). The simplest and the most commonly assumed model for a mixed spectrum is a linear model. A single pixel can be portrayed as a checkerboard mixture, as illustrated in Figure 70 and assuming that there is no multiple scattering between components, then the spectral response of the pixel is a linear combination of the fractional abundances (area covered by each endmember in the pixel) of the individual substances, hence the term Linear Mixture Model (LMM).

3. Binary Encoding

The binary encoding classification technique encodes the data and endmember spectra into zeros and ones, based on whether a band falls below or above the spectrum mean, respectively. An exclusive OR function compares each encoded reference spectrum with the encoded data spectra and produces a classification image. All pixels are classified to the endmember with the greatest number of bands that match, unless you specify a minimum match threshold, in which case some pixels may be unclassified if they do not meet the criteria.