

# MULTISPECTRAL ANALYSIS OF SATELLITE IMAGES

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## ABSTRACT :

Spectroscopy by satellite images has many new and exciting applications. Areas such as agriculture, forestry, geology and many others have great potential for new research advances using this technology. There are several common issues though, that need to be addressed on a regular basis in order to achieve valuable research results.

This work presents a multispectral analysis of natural targets behavior of a study area, using the TM sensor images (Thematic Mapper) on board the satellite LANDSAT 5. The spectral classification was done according to the following steps :

- a) spectral reduction by the *Minimum Noise Fraction* (MNF) transformation,
- b) spatial reduction by the Pixel Purity Index (PPI) and
- c) manual identification of the endmembers using the N-dimensional visualizer.

These procedures allowed showing the kind of landscape that presents a strong correlation with geology.

Keywords : Landast TM Multispectral Images, MNF transformation, PPI, endmembers, Reflectance spectrum, ENVI software

## 1- INTRODUCTION

With a multispectral analysis of an images collected by radiometers and detectors embarked on a satellite, one can make : " *spectroscopy by satellite imagery* ". Imaging spectrometers or "multispectral sensors" are remote sensing instruments that combine the spatial presentation of an imaging sensor with the analytical capabilities of a spectrometer. With a radiometer such as AVIRIS " Airborne Visible/Infrared Imaging Spectrometer " where the number of spectral bands exceeds the 200, and with a spectral resolution on the order of 10 nm or narrow, it can produce a complete spectrum for each pixel of the image. the case of this radiometer enters on the "*Hyperspectral*" field. In the case of our study, we are using the radiometer TM (Thematic Mapper), which is on board the satellite Landsat 5, and which only has 7 multispectral bands, with a spectral resolution on the order of 100 nm. Like finale result, one using the spectroscopy by satellite imagery, we can identify the spectra of various materials which are on various terrestrial surfaces.

However there are several common issues though, that need to be addressed on a regular basis in order to achieve valuable research results. One always needs high quality data, the proper radiometric, geometric and atmospheric corrections, and appropriate analysis techniques in order to achieve acceptable results. The purpose of this work is to present and explain the main analysis techniques available for multispectral imagery. This will be done using ENVI 3.1 software (the **Environment for Visualizing Images**), which is a well-known hyperspectral analysis program. The analysis techniques will include :

- minimum noise transformation,
- pixel purity index and
- n-dimensional visualization.

## 2. DATA TO ANALYZE

In our study, we will treat a satellite image representing a part of the region of Laghouat (Algeria), taken by the satellite Landstat 5 on April 12, 2001. It is represented

by its 6 channels images TM (Thematic Mapper 1, 2, 3, 4, 5, 7). The infrared thermal channel TM6 will not be treated in our study. Here we will create Color-Ratio-Composite (CRC) Images using standard TM band-ratio images. This method tries to get around the limitations of relatively broad spectral bands in Landsat TM data by using ratios of bands to determine relative spectral slope between bands and thus the approximate shape of the spectral signature for each pixel. Common band-ratios include: Band-Ratio 5/7 for Clays, Carbonates, Vegetation; Band-Ratio 3/1 for Iron Oxide; Band-Ratios 2/4 or 3/4 for Vegetation; and Band-Ratio 5/4 also for vegetation.

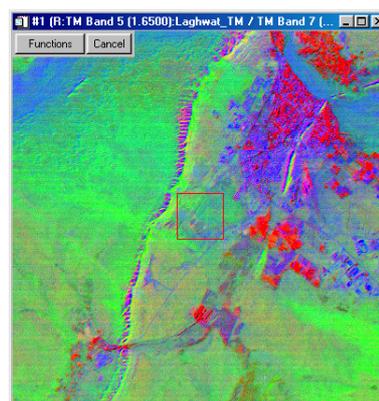


Figure.1. shows the combination of 5/7, 3/1, 2/4 (RGB) results in an image in which clays/carbonates are magenta, iron oxides are green, and vegetation is red. Other ratio combinations and color schemes can be designed to highlight specific materials.

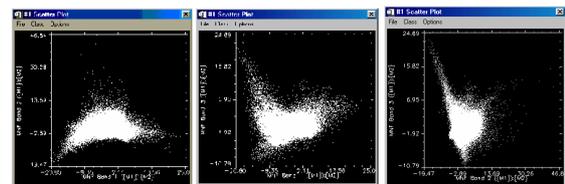
## 3. ANALYSIS

Since the goal of our work is to extract a reflectance spectrum, the treated image must be calibrated in

reflectance mode (each pixel of the image is presented by a value of reflectance). At the end of this study, resulting reflectance spectra should be identified to a various objects and terrestrial materials, for that, ENVI 3.1 has a "spectral Libraries ". These libraries contain a whole of various experimental calculated spectra reflectance, representing a various materials terrestrial: minerals, vegetation, rocks, water...Once the images has been opened in ENVI 3.1, analysis techniques can then be applied to the data. These techniques will be explained in detail below. They consist of minimum noise fraction transformation, pixel purity index, and n-dimensional visualization. Overall, these analyses eliminate noise, select pure pixels, create endmembers, visualize the endmembers, and compare endmembers to various spectral libraries.

### 3.1. Minimum Noise Fraction Transformation

The minimum noise fraction (MNF) transformation is used to determine the inherent dimensionality of image data, to segregate noise in the data, and to reduce the computational requirements for subsequent processing (See Boardman and Kruse, 1994). This step is often completed as a precursor to other types of analysis. Basically it is a way of simplifying the data. The MNF transform is essentially two principal component transformations. The first transformation, based on an estimated noise covariance matrix, decorrelates and rescales the noise in the data. This first step results in transformed data in which the noise has unit variance and no band-to-band correlations. The second step is a standard principal components transformation which creates several new bands containing the majority of the information. For the purposes of further spectral processing, the inherent dimensionality of the data is determined by examination of the final eigenvalues and the associated images. The data space can be divided into two parts: one part associated with large eigenvalues and coherent eigenimages, and a complementary part with near-unity eigenvalues and noise-dominated images. By using only the coherent portions, the noise is separated from the data, thus improving spectral processing results. Once applying MNF technique, on the 6 bands images TM (which must be calibrated in reflectance mode), we will have like result 6 new bands images MNF. The image pixels are presented by eigenvalues. For the purposes of further spectral processing, the dimensionality of the data is determined by examination of these values. In examining the eigenvalues it can be seen that the first MNF bands ( 1 and 2) have the highest values while the remaining bands have consistent low values. It is the first two bands with the large values that contain most of the information and it is these bands that correspond to MNF images. The remaining low value bands (3 and under for example) are seen as noise. The images show the information compressed into only a few bands. The redundancy of the data is eliminated and noise is also removed. The result are more interpretable images. You could say that the data has been simplified or the dimensionality has been reduced. After the data has been transformed, it is possible to examine scatterplots between each fraction image in order to understand the images better. Figure.2 shows scatterplots between the first three bands :



a) Band 1 .vs. Band 2    b) Band 1 .vs. Band 3  
c) Band 2 .vs. Band 3

Figure.2 Scatterplots of MNF bands

The scatterplots plot the data of different MNF bands against each other. This gives an ideas of the spectral data distribution. Of special interest are the arms or separate clusters outside of the main data cloud. These areas represent unique spectra called "endmembers" which represent unique ground components. From the scatterplots the user can manually highlight endmembers and identify them on the image.

### 3.2. PIXEL PURITY INDEX (PPI)

All remotely sensed images contain a phenomenon known as mixed pixels. These are pixels that contain a mix of features (e.g. grass, forest water). In multispectral analysis it is useful to separate purer from more mixed pixels in order to reduce the number of pixels to be analyzed for endmember separation and identification. The pixel purity index is a way of finding the most spectrally pure pixels in images (Boardman, 1993; Boardman & *al.*, 1995). The PPI stipulates how many times the pixel is extreme in the simplex (Boardman & Kruse, 1994; Boardman *et al.*, 1995). The most spectrally pure pixels typically correspond to spectrally unique materials. The PPI procedure generates an image where pixel values correspond to the number of times that this pixel was recorded as extreme. This way, threshold of the PPI image can stipulate the most extreme pixel results in further spatial reduction. In this paper the PPI was performed using the six bands MNF. The PPI was processed with 100 iterations. The PPI image was generated using the threshold of 3. Brighter pixels represent more spectrally extreme "hits" and indicate pixels that are more spectrally pure. Darker pixels are less pure. The value of the pixel corresponds to the number of times it was recorded as extreme during the PPI process.

### 3.3. N-DIMENSIONAL VISUALIZATION

The n -Dimensional Visualizer is an interactive tool that allows the user to select endmembers in n-space. This procedure generates clouds of points related to the pixels in a n-dimensional space defined by the MNF components. Once we have chosen the bands to display, the visualizer can then go to work, it rotates interactively the data cloud. The user is able to see the spectral data in many dimensions from many angles. From here one can interactively select endmembers. From different angles we are able to visualize and highlight (in different colours) the distinct spectra which appears as an endmember (Figure.3)

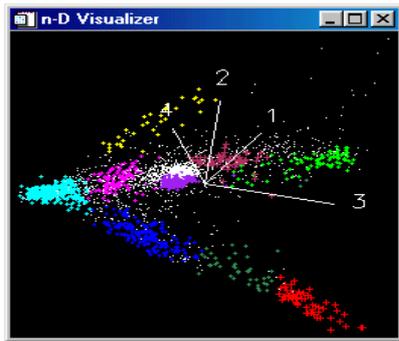


Figure 3. Endmember selection using n-d visualizer

#### 4. RESULTS

After endmembers have been selected, comparisons can be made between the endmember spectra ( figure.4) and various library spectra. ENVI 3.1 provides several spectral libraries for comparison. In our study, we have chosen the USGS spectral library which contain a great number of mineral and vegetation Reflectance spectra. A pixel of coordinates (x,y) (row, line), presented by a Reflectance spectra traced in bleu, is identified with a mineral reflectance spectra traced in black. For example, we could now identify some mineral components of the Color-Ratio Composite Image of ratios 5/7, 3/1, and 2/4 represented before in Figure 3 and (Table 1)

Table 1. Identification of some components of the coloration composite image.

Clays	Carbonate	Iron Oxyde	Vegetation
Illite 5 Glaucofane	Dolomite	Cuprites	Lawn grass Cheat grass

For vegetation, we have identified only two Reflectance spectra, in view of the fact that Laghouat is a sub-Saharan region (poor in vegetation).

#### 5. CONCLUSION

Spectroscopy by satellite images brings a new conception in remote sensing that enables the identification of the major scene components. It has a great potential to aid numerous other fields of study. The success of research is very much dependent on the quality of data, correctness of data and the analysis techniques used. The employment of the sequence of MNF, PPI and n-D visualizer in the study area allowed the identification of different mineral and vegetation. This work showed a possible cartography of soil occupation using objects spectral library and a sequential technique in processing image.

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These spectra were measured on a custom-modified, computer-controlled Beckman spectrometer at the USGS Denver Spectroscopy Lab. Wavelength accuracy is on the order of 0.0005 micron (0.5 nm) in the near-IR and 0.0002 micron (0.2 nm) in the visible. which we had recourse before, we can identify a great number of spectra representing various minerals.

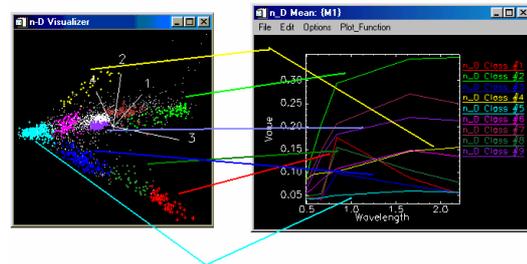


Figure.4. Identification of endmembers reflectance spectra with a mineral reflectance spectra (using USGS spectral library)

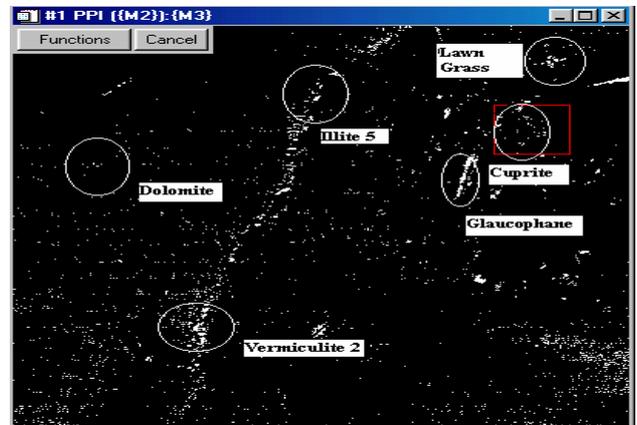


Figure 5. Score image for mineral/vegetation endmember.

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