Spatial-spectral contextual image analysis of hyperspectral data to aid in the characterisation of hydrothermal alteration in epithermal gold deposits

Freek van der Meer, Harald van der Werff & Frank van Ruitenbeek
International Institute for geoinformation science and earth observation (ITC), POBox 6, Enschede, the Netherlands, phone: +31534874353, Fax: +31534874336, email: vdMeer@itc.nl

Abstract: Hyperspectral remote sensing deals with instruments that sample the EM spectrum at high spectral resolution and with high spectral sampling intervals to produce surface reflectance data that can be readily compared to spectral signatures contained in spectral libraries. In geology, this technology has been used for mineral mapping and geobotanical studies to aid in mineral prospecting, environmental studies and petroleum exploration. Most image processing techniques that are available to analyse hyperspectral data by-pass three important aspects of remote sensing:

1. Neighbourhood information is not incorporated and hence the common knowledge formulated in geostatistics that nearby control points are more likely to contain information more similar than far apart control points,
2. surface information is not coupled to shallow subsurface information although many problems are in need of a 3 dimensional approach of study
3. and the change over time of the spectral signature of certain earth surface materials that contains information on the type (and use) of the material at hand that may allow a better classification and or discrimination (from other) of materials is not used in sub pixel classification.

This paper addresses our efforts in designing spatial-spectral contextual image analysis approaches, thus tackling some of the aspects mentioned under 1. To combine both spectral as well as spatial information in the analysis of hyperspectral imagery we have developed a spatial spectral algorithm; the template matching algorithm. A template consists of a one or two dimensional array that is filled on both sides of a central pixel with spectra (or spectral derivatives such as ratios etc) that characterize certain cover types of interest. The template is matched with an image by moving the kernel or a filter over the image and calculating parameters at each pixel. At each pixel the template is also rotated and a number of parameters are calculated (e.g., best template fit, worst template fit, mean template fit, variance in template fit, and optimal scanangle). Examples are given to the application of template matching as a spatial-spectral contextual image processing technique dealing with the detection of mineral assemblage coexistence in relation to hydrothermal alteration in a epithermal gold deposit.
Keywords: Hyperspectral remote sensing, contextual image analysis, hydrothermal alteration, gold mineralization

1. Introduction

The first advanced earth observation techniques were developed in the late sixties and early seventies and resulted in the launch of the first Earth observation satellite Landsat in 1972. Ever since, earth observation has gained importance in a wide variety of environmental studies such as Geography, Geology, Hydrology, Geochemistry etc. A major step forward was made in the late eighties when new technologies such as Imaging Spectrometry and Interferometric SAR were developed into operational systems. These earth observation systems allow a significant improved, quantitative approach of collecting information of objects at the earth surface compared to more traditional remote sensing sensors. Imaging Spectrometry and/or Interferometric SAR can for example be used to quantify Leaf Area Indices of natural vegetation and agricultural crops, to quantitatively map abundance of minerals or to measure small deformations of the earth surface crust due to earthquakes of geological faulting. These developments have made modern and advanced earth observation important products for monitoring changes in the earth ecosystem (land degradation, land cover change, deforestation, water quality) and for collecting input data for a wide range of landscape simulation models (flooding, soil erosion, evapo(transpi)ration, crop growth models).

Spectroscopy is the study of light as a function of wavelength that has been emitted, reflected or scattered from a solid, liquid, or gas. As photons enter an object i.e. a leaf or a mineral, some photons are reflected from surfaces, some pass through the surface, and some are absorbed. Those photons that are reflected from surfaces or refracted through a particle are said to be scattered. Scattered photons may encounter another object or be scattered away from the surface so they may be detected and measured. Photons may also originate from a surface, a process called emission. All natural surfaces emit photons when they are above absolute zero. Emitted photons are subject to the same physical laws of reflection, refraction, and absorption to which incident photons are bound. At geographical levels of scales these interactions of radiance with objects may be registered by remote sensing devices and provide us with information about an object identity or object properties providing synoptic overviews of our living environment.

Reflectance spectra have been studied in the laboratory and field in a wide variety of fields. In natural sciences and geosciences, reflectance spectra are used in:

- Geology; to determine the mineralogy of a sample, to derive the chemical composition of a mineral, mineral mixture or rock ;
- Vegetation sciences; to foster vegetation species mapping, to collect structural vegetation properties and to derive biochemical compounds in leaf and canopy;
- Soil sciences; to determine the mineralogy of soils, to quantify the chemical composition of soils;
- Hydrology; to quantify chlorophyll, suspended sediments in water in relation to water quality.

Further details can be found in e.g. [5].

From the earlier work on field and laboratory spectroscopy, imaging devices were developed that acquire high spectral resolution imaging data in the VIS/NIR, SWIR and TIR regions; hyperspectral scanners. This opened up the possibility to map the above listed parameters and better understand their spatial and dynamic configuration, and hence improving our insight in the underlying earth science processes. The first techniques deployed for the analysis of hyperspectral imagery were exclusively pixel-based techniques, which implies that the spatial context or neighbourhood information was excluded from the analysis. Thereafter the use of geostatistical tools allowed to get a handle on spatial variability in image data and allowed to combine image and field data through co-regionalisation and fractal behaviour. More recently we have been working on spectral-spatial contextual image analysis approaches in the hyperspectral domain. We now have a number of techniques that allow to combine spatial context of an image and spectral information for object-based image analysis and classification [4].

The power of remote sensing lies in its ability to monitor processes and hence provide objective information on the continuously changing three-dimensional landscape. Most, if not all, classification methods do not incorporate the fourth time dimension in the analysis. Classification, whether this is hard classification (maximum likelihood, neural network etc.) or soft classification (fuzzy, spectral unmixing etc.), deals with single remote sensing data sets acquired at one single instance in time and results in fractional abundance estimates or classified pixels for that time instance.

However most image processing techniques available to analyse high-spectral resolution data sets, to process time series of remote sensing data and to produce thematic land cover and land use products by-pass two important aspects of remote sensing:

- Neighbourhood information is not incorporated and hence the common knowledge formulated in geostatistics that nearby control points are more likely to contain information more similar than far apart control points;
- Surface information is not coupled to shallow subsurface information although many problems are in need of a 3 dimensional approach of study;
- And the change over time of the spectral signature of certain earth surface materials that contains information on the type (and use) of the material at hand that may allow a better classification and or discrimination (from other) of materials is not used in (sub pixel) classification.

Hence in this paper we concentrate on developing techniques that allow context-based remote sensing time series analysis taking full advantage of the spatial information on objects available in satellite data. We have developed contextual object-based image processing techniques in 2D (e.g., the spatial domain) and propose to extend these to the 3D space-time domain including the development of proper tools for accuracy assessment, thus leading to validate object reconstruction in space and time. We first discuss some of the common approaches in hyperspectral remote sensing that are based on a pixel by pixel deconvolution of image data. From there we look at stratified approaches and finally look at contextual approaches that deploy both spectral as well as spatial image content.

2. Processing of hyperspectral imagery

Various approaches exist to the analysis of hyperspectral data including spectral matching techniques, spectral unmixing techniques, image stratification and contextual approaches.

2.1 Spectral matching techniques used for compositional mapping

There are various techniques to process hyperspectral imagery in order to obtain surface compositional information on a pixel-by-pixel basis for the entire image. Techniques that specifically use absorption band position and depth include (1) the Relative Absorption Band-Depth (RBD) approach of [2], (2) the Spectral Feature Fitting (SFF) technique of [1] and (3) the TRICORDER [3] and TETRACORDER algorithms developed at the USGS spectral laboratory. These techniques work on so-called continuum removed reflectance spectra, thus acknowledging that the absorption in a spectrum has two components: a continuum and individual features.

Another spectral matching technique is the Cross correlogram spectral matching (CCSM; [7]); an approach toward mineral mapping from imaging spectrometer data using the cross correlogram of pixel and reference spectra.

The most used mapping method in hyperspectral remote sensing is the spectral angle mapper. The Spectral Angle Mapper calculates the spectral similarity between a test reflectance spectrum and a reference reflectance spectrum assuming that the data is correctly calibrated to apparent reflectance with dark current and path radiance removed.

2.2 Spectral unmixing

The most widely used method for extracting surface information from hyperspectral images is image classification. With this technique, despite the stochastic concept of the method, each pixel is assigned to one out of several known categories or classes through a statistical separation approach. Thus an image is decomposed into an image containing only thematic information of the classes previously selected as the expected image elements. In general, a training sample set of pixels is defined by the user to train the classifier. The spectral characteristics of each training set are defined through a statistical or probabilistic process from feature spaces and unknown pixel to be classified are statistically "compared" with the known classes and assigned to the class to which they mostly resemble. In this way thematic information is obtained disregarding the mostly compositional nature of surface materials. Reflected radiation from a pixel as observed in remote sensing imagery has rarely interacted with a volume composed of a single homogenous material because natural surfaces composed of a single uniform material do not exist in nature. Most often the electromagnetic radiation observed as pixel reflectance values results from the spectral mixture of a number of ground spectral classes present at the surface sensed.

Rather than aiming at representing the landscape in terms of a number of fixed classes, mixture modeling and spectral unmixing acknowledge the compositional nature of natural surfaces and strive at finding the relative or absolute fractions (or abundance) of a number of spectral components or end-members that together contribute to the observed reflectance of the image. Therefore the outcome of such analysis is a new set of images that for each selected end-member portray the fraction of this class within the volume bound by the pixel. Mixture modeling is the forward process of deriving mixed signals from pure end-member spectra while spectral unmixing aims at doing the reverse, deriving the fractions of the pure end-members from the mixed pixel signal. A linear combination of spectral end-members is chosen to decompose the mixed reflectance spectrum of each pixel, R_i, into fractions f_j of its end-members, Re_{ij}, by

$$R_i = \sum_{j=1}^{n} f_j \, \mathrm{Re}_{ij} + \varepsilon_i \quad \text{and} \quad 0 \le \sum_{j=1}^{n} f_j \le 1 \qquad (1)$$

where R_i is the reflectance of the mixed spectrum in image band i for each pixel, f_j is the fraction of each end-member j calculated band by band, Re_{ij}, is the reflectance of the end-member spectrum j in band i, i is the band number, j is each of the n image end-members and f_j is the residual error or the difference between the measured and modelled DN in band i. A unique solution is found from this equation by minimizing the residual error, ε_i, in a least-squares solution. This residual error is the difference between the measured and modelled DN in each band and should in theory be equal to the instrument noise in case that only the selected end-members are present in a pixel. Residuals over all bands for each pixel in the image can be averaged to give a root-mean square (RMS) error, portrayed as an image, which is calculated from the difference of the modelled (R_{jk}) and measured (R_{jk}') pixel spectrum as

$$RMS = \sum_{k=1}^{m} \frac{\sqrt{\sum_{j=1}^{n} (R_{jk} - R_{jk}')^2 / n}}{m} \qquad (2)$$

where n is the number of spectral bands and m the number of pixels within the image.

2.3 Stratified analysis of hyperspectral imagery

An alternative approach to thematic analysis of hyperspectral data is stratified analysis. The aim would be to stratify the data on known thematic data layers prior to analytical approaches being applied to the data. In many cases, field or thematic map data is available. This data can thus be used for data processing. One can imagine clustering a data set on mapping units and start analysing within these natural boundaries. Furthermore various data products from hyperspectral data sets can be integrated using statistical techniques.

2.4 Contextual analysis of hyperspectral imagery

Stratified approaches are one step in the direction of using prior and thematic information in the analysis of hyperspectral data sets. A next step would be to include spatial and contextual information. These pixel-based methods have in common that they yield surface compositional information (e.g., in geologic applications this is often surface mineralogy) that has to be further translated into a geologic model (which involves understanding the

spatial context of surface mineralogy). Furthermore, these models bypass the common notion in geology that spatial (contextual) information provides valuable information to infer the transitional nature of geologic context. In other words, field geologists working in, for example, hydrothermal alteration systems use mineral paragenesis and the mineral assemblage in their mapping. When identifying a certain suite of minerals at a location not only do they know in which part of the alteration system they spatially are, but also from this information they can infer which mineralogic transition they are about to discover when progressing through the terrain. Hence, not only do they use information on the surface mineralogy, but also they use neighborhood information to unravel the geologic history and alteration system of an area.

A first technique to include spatial information in the analysis of hyperspectral data sets uses Bayesian inversion. Assuming that a set of physical measurements {**m**} can be inverted to their resulting variables {**x**} if the underlying physical process is known and the following relationship is assumed

$$\mathbf{m} = \Phi(\mathbf{x}) + \mathbf{n} \qquad (3)$$

where **n** is the sensor noise. The direct inversion in the presence of (random) noise results in

$$\mathbf{x} = \Phi(\mathbf{m})^{-1} + \mathbf{n} \qquad (4)$$

In [6] a Bayesian approach has been discussed for data inversion using a artificial neural network.

The input of geologic knowledge into the process will be described in the following subsections. The mismatch of the inversion model is defined as the difference between the physical measurements $\phi(\mathbf{x}_i)$ and the estimated geologic-physical model $\hat{\phi}(\mathbf{x}_i)$, hence $\phi(\mathbf{x}_i) - \hat{\phi}(\mathbf{x}_i)$. The neural network is used to iteratively reduce this mismatch propagating the geologic model through the imaging spectrometry data.

The input layer of the neural network comprises of one node, i, for each discriminating variable, while the one or more hidden nodes, j, each contain a user-defined number of units. The output layer contains one node, k, for each geologic class. The ANN we use employs a classical back-propagation algorithm where a desired output is defined the on basis of training (geologic) input data (classes) and for each *k* class the desired output vector $\mathbf{d}_k$ is defined. Each training pixel is propagated through the net and the derived output vector $\mathbf{o}_k$ is found which in turn is used to find the error term ε which is based on the difference between the true and expected output vectors. The weights between these layers, w_{ji} and w_{kj} are adjusted after each iteration by

$$\Delta w_{kj} = LR \sum_{p=1}^{p} (\mathbf{d}_k - \mathbf{o}_k) \frac{d}{dS} f(S)\Big|_{S_k} h_j \qquad (5)$$

and

$$\Delta w_{ji} = LR \sum_{p=1}^{p} \frac{d}{dS} f(S)\Big|_{S_k} \sum_k [(\mathbf{d}_k - \mathbf{o}_k) \frac{d}{dS} f(S)\Big|_{S_k} w_{kj}] p_i \qquad (6)$$

respectively, where *LR* is the learning rate (used to control the speed of convergence), $f(S)$ is the sigmoid activation function conveniently defined as $f(S) = \frac{1}{1+e^{-S}}$, p_i are the i input patterns $i = 1 \ldots P$ assuming a set of p_i vector-pairs, (x_1,y_1), (x_2, y_2), ..., (x_p, y_p), which are examples of a functional mapping y = $\Phi(x) : x \in R^N$, $y \in R^N$ and assume we train the network so that it will approximate 0 = y' = $\Phi'(x)$ by finding a set of weights that fits a number of known observations. The iteration of the network is repeated until the error ε does not exceed a pre-defined threshold value. The model strives at maximising

$$\max_{\forall \mathbf{x}_i} . f(\mathbf{x}_i | \mathbf{m}, \mathbf{y}) = f(\mathbf{m} | \mathbf{x}_i) f(\mathbf{y} | \mathbf{x}_i) f(\mathbf{x}_i) \qquad (7)$$

Thus maximization of the conditional probability of the set of variables {$\mathbf{x}_i$}given the set of measurements {**m**} within a neighborhood **y** is equivalent to minimizing the mismatch between (geologic-physical) model and observation (allowing some mismatch due to sensor noise), $f(\mathbf{m} | \mathbf{x}_i)$, given a prior probability, $f(\mathbf{x}_i)$, for the variables, $\mathbf{x}_i$, and a neighborhood distribution, $f(\mathbf{y} | \mathbf{x}_i)$, which is arbitrarily inferred from a kernel of 8 surrounding pixels.

3. A new template method to introduce spatial information in the analysis of hyperspectral data sets

3.1 The template matching algorithm; theory

We have progressed considerably over the last years in including neighbourhood information in the analysis of hyperspectral data sets. Hence in this research project we intend to extent the spatial-contextual image analysis methods to the *temporal* domain as well as to the third dimension (i.e., the shallow subsurface). In this research project, we propose to develop ways in which we include both the spatial as well as the temporal (time) aspects in the analysis and processing of time series of remote sensing data sets. Building on the theoretical framework of spatial-contextual image analysis, we introduce the temporal endmember which is a 2D signature combining the spectral uniqueness of a class with its variability in the temporal domain. To combine both spectral as well as spatial information in the analysis of hyperspectral imagery we have developed a spatial - spectral algorithm; the template matching algorithm ([8], [9]). As shown in figure 1 the template consists of a one or two dimensional array that is filled on both sides of a central pixel with spectra that characterize certain cover types of interest. The template is matched with an image by moving the kernel or a filter over the image and calculating parameters at each pixel. At each pixel the template is also rotated and the following parameters are calculated:

- the best template fit;
- the worst templ ate fit;
- the mean template fit;
- the variance in template fit;
- the mean variance in fit of individual pixels;
- the variance in variance in fit of individual pixels;
- the optimal scanangle, which is the angle belonging to the best template fit.
-

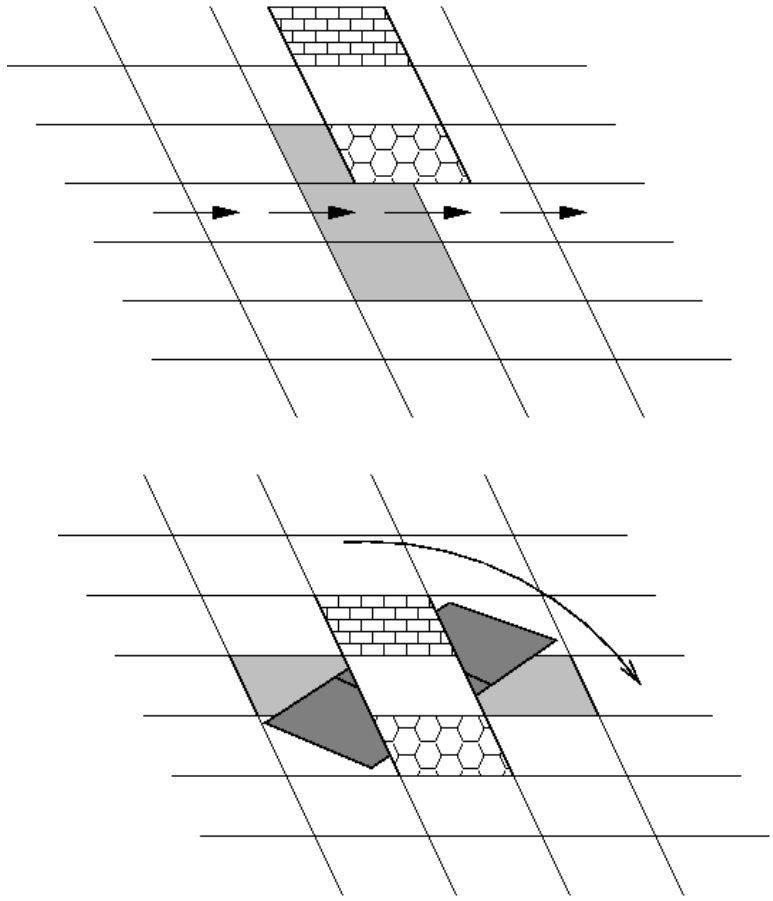

Figure 1: Concept of template matching using a rotational kernel at each image pixel location.

The template fit [angle (rad)] is the total or overall value for *N* number of pixels. The mean fit $\left(\overline{F_p}\right)$ is calculated for *N* number of pixels with already calculated spectral matching fit $F_{(p)}$ using the following equation:

$$\overline{F}_p = \frac{\sum_{p=0}^{N} F_{(p)}}{N} \tag{8}$$

The variance in pixel fit $\left(V_p\right)$, the Templatefit Variance layer, is calculated for the template as:

$$V_p = \frac{\sum_{p=0}^{N} (F_{(p)} - \overline{F}_p)^2}{N} \tag{9}$$

When template is rotated, for every orientation (every scan angle) of template $\left(\overline{F_p}\right)$ and $\left(V_p\right)$ are calculated. The extreme values for $\left(\overline{F_p}\right)$ are stored as "Best Template Fit" and "Worst Template Fit". The optimal scanangle is set to the scan angle (best orientation) that gave "Best Fit Template", otherwise variance in template fit can not be determined. The "Mean Template Fit" is calculated using:

$$\overline{F}_T = \frac{\sum_{a=0}^{A} \overline{F}_{p(a)}}{A} \tag{10}$$

Where *A* is the number scan angles, the variance in template fit $\left(V_T\right)$ is calculated by:

$$V_T = \frac{\sum_{a=0}^{A} (\overline{F}_{p(a)} - \overline{F}_T)^2}{A} \tag{11}$$

Figure 2 shows a number of examples of the template matching approach for an image profile (one image line) with varying transition types (fuzzy, crisp) between land units.

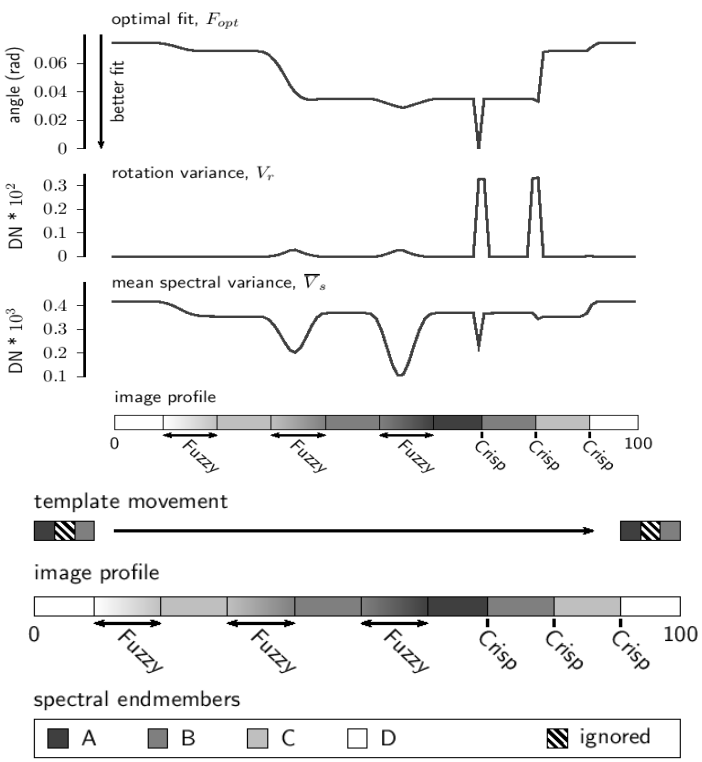

Figure 2: Results of template matching on synthetic image line showing the improved capabilities for detecting crisp and fuzzy boundaries.

3.2 The template matching algorithm; application

The area of study is located in the Sierra del Cabo de Gata (Cabo de Gata national parc; Figure 3), in the south-eastern corner of Spain, consisting of calc-alkaline volcanic rocks of the late Tertiary age (absolute dating suggest a cooling age between 15 to 7 Ma.) comprising the Almeria-Cartagena volcanic belt. The volcanic rocks range in composition from pyroxene andesites to rhyolites. Extensive hydrothermal alteration in the volcanic hosts rocks has resulted in new formation of metamorphic minerals from high to low temperature as silica, alunite, kaolinite, montmorillonite and chlorite. Associated with this mineral alteration assembly are gold deposits and low-sulphidation Pb-Zn quartz veins. The high sulphidation gold deposits are located in the central part of the volcanic field within the so-called Rodalquilar caldera. Five alteration facies can be distinquished: silicic, advanced argillic, intermediate argillic and propylitic.

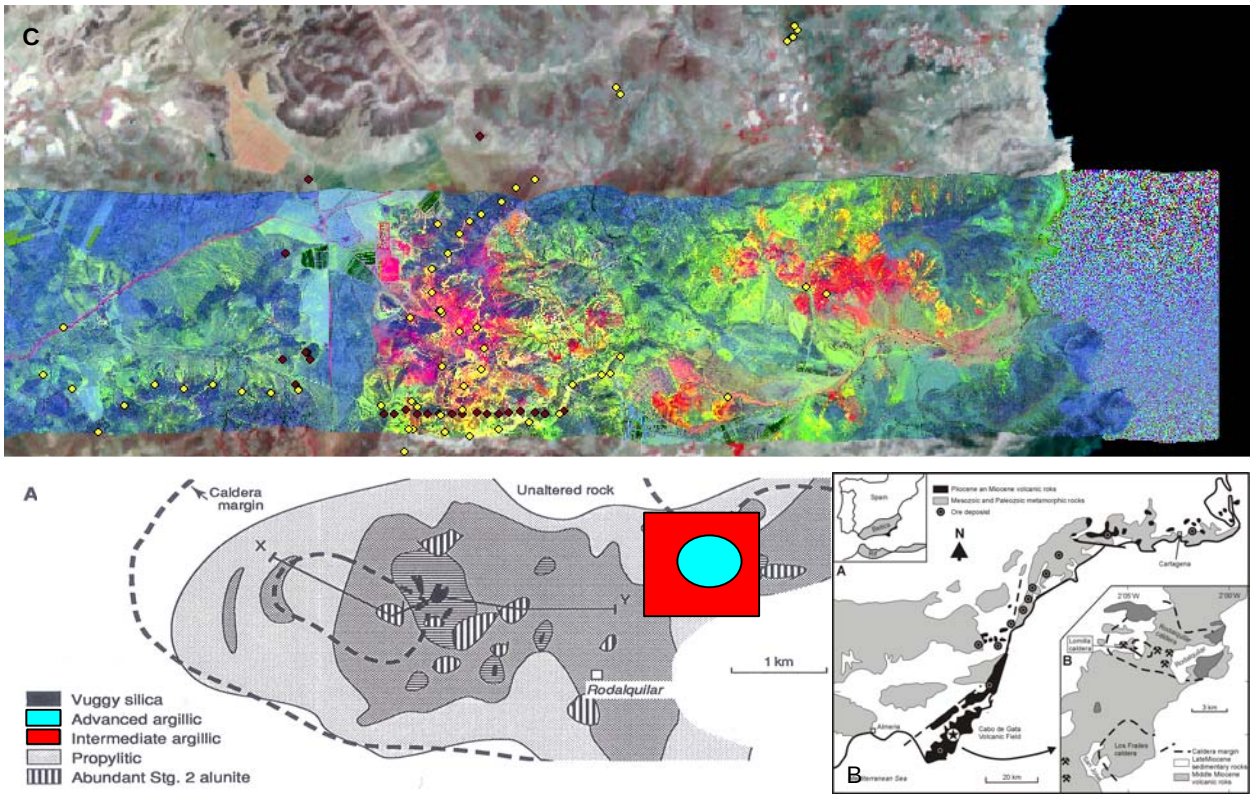

Figure 3: (A) Hydrothermal alteration map of the Rodalquilar area in southern Spain, (B) map showing the tectonic setting of the Rodalquilar area, (C) Aster image with hymap strip overlain (color coding signifies the intensity of alteration from low=blue through medium=yellow to high=red).

We use airborne imaging spectrometer data from HyMAP acquired in July 2003 during the HyEUROPE 2003 campaign (Figure 3). The Hyperspectral Mapper (HyMAP) is a 126-channel instrument that collects data in a cross-track direction by mechanical scanning and in an along-track direction by movement of the airborne platform. The instrument acts as an imaging spectrometer in the reflected solar region of the electromagnetic spectrum (0.4 to 2.5 µm) and collects broadband information in the MIR (3 - 5 µm) and TIR (8 - 10 µm) spectral regions. Spectral coverage is nearly continuous in the SWIR and VNIR regions with small gaps in the middle of the 1.4 and 1.9 µm atmospheric water bands. The spatial configuration of the instrument gives an IFOV of 2.5 mrad. along track and 2.0 mrad. across track resulting in a pixel size in the order of 3-5 m. for the data presented in this paper. It should be noted that due to instrument failure the SWIR 1 detector did not function during acquisition, thus no data were acquired in the 1500-1760 nm window. The HYMAP data was atmospherically and geometrically corrected using the ATCOR 4 model.

Using a subset of the HyMAP data we have run the template over the image using a kaolinite-illite boundary as well as a kaolinite-alunite boundary. The results are shown in Figure 4. the combination of the rotation variance, the optimal template fit and the mean spectral variance are portrayed. The spectral variance is a measure for the pureness of a pixel, the rotation variance shows the boundaries of the mineral classes. Figure 5 illustrates this along a profile through the image subset.

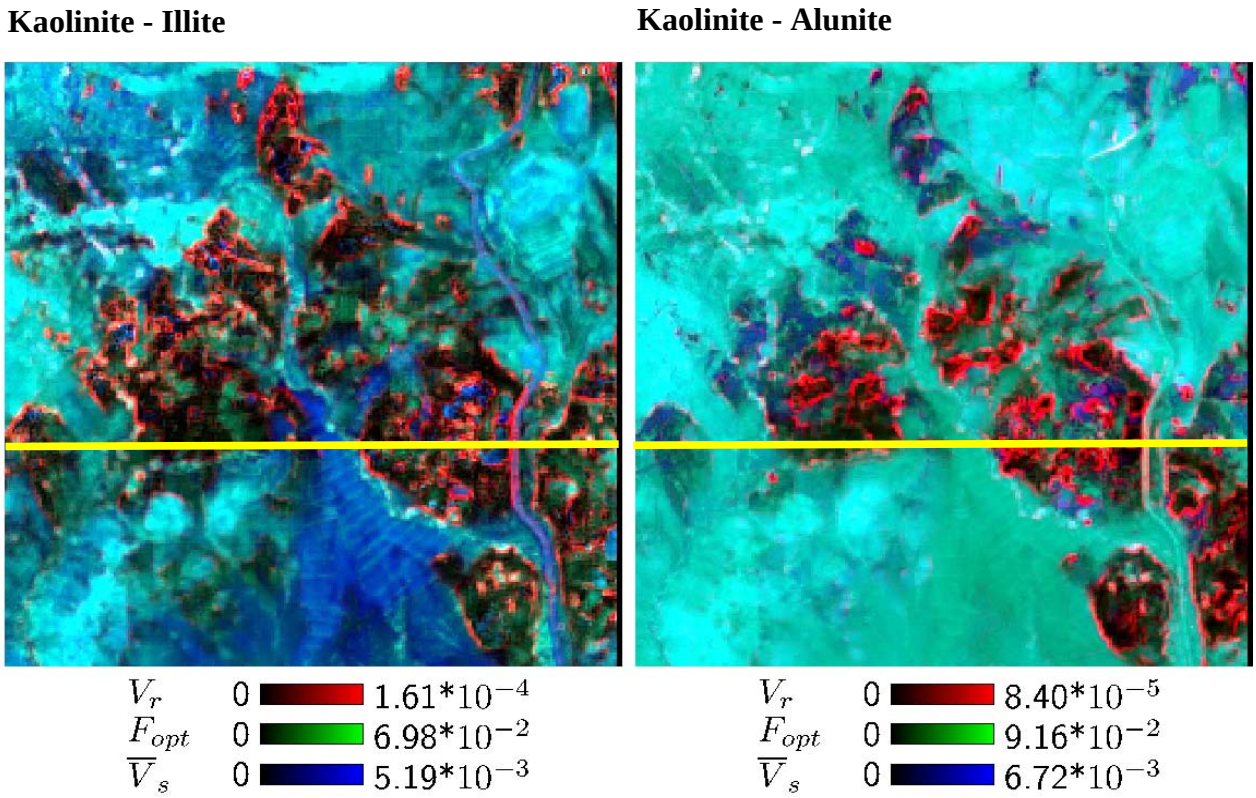

Figure 4: Color composite of Kaolinite-illite (left) and kaolinite-alunite (right) boundaries mapped with the template method at the Rodalquilar area. Yellow line is the cross section shown in Figure 5; results after [9]).

4. Conclusions

In this paper we have provided an overview of image processing strategies that are currently being used to analyse hyperspectral data sets. Most of these image processing techniques that are available to analyse hyperspectral data by-pass three important aspects of remote sensing: neighbourhood information is not incorporated and hence the common knowledge formulated in geostatistics that nearby control points are more likely to contain information more similar than far apart control points, surface information is not coupled to shallow subsurface information although many problems are in need of a 3 dimensional approach of study, and the change over time of the spectral signature of certain earth surface materials that contains information on the type (and use) of the material at hand that may allow a better classification and or discrimination (from other) of materials is not used in sub pixel classification. This paper addressed our efforts in designing spatial-spectral contextual image analysis approaches, thus tackling some of the aspects mentioned under 1. To combine both spectral as well as spatial information in the analysis of hyperspectral imagery we have developed a spatial spectral algorithm; the template matching algorithm. A template consists of a one or two dimensional array that is filled on both sides of a central pixel with spectra (or spectral derivatives such as ratios etc) that characterize certain cover types of interest. The template is matched with an image by moving the kernel or a filter over the image and calculating parameters at each pixel. At each pixel the template is also rotated and a number of parameters are calculated (e.g., best template fit, worst template fit, mean template fit, variance in template fit, and optimal scanangle). Examples are given to the application of template matching as a spatial-spectral contextual image processing technique dealing with the detection of mineral assemblage coexistence in relation to hydrothermal alteration in a epithermal gold deposit. These show that including spatial as well as spectral information in the analysis of hyperspectral data is both feasible as well as encouraging in terms of results obtained.

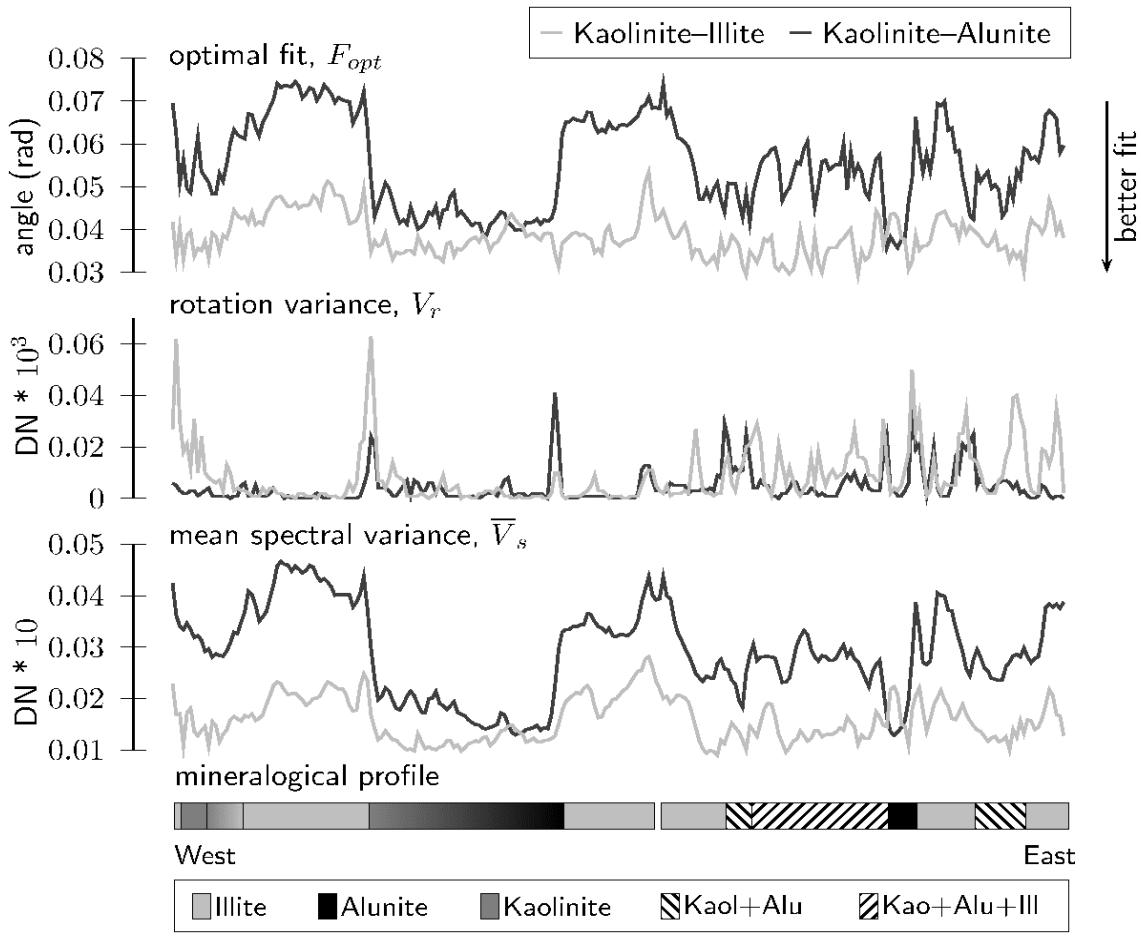

Figure 5: Transect through the images of Figure 4 showing that the optimal fit and the spectral variance are indicator of the pureness of a pixel thus highlighting the various classes while the rotation variance shows the boundaries between classes (after [9]).

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