A PRACTICAL ALGORITHM FOR MINERAL DETECTION IN HYPERSPECTRAL ANALYSIS

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Abstract: Hyperspectral imaging has opened a new outlook for mineral detection in geological studies and mineral deposit explorations regarding to its spectral information. An exploration project is generally started by rationally fast and cheap studies and continued toward precise and of course expensive activities like bore holes drilling and tunnelling. They are faster and cheaper than other prospecting methods. Developing of image processing methods for hyperspectral data on the other hand has made remote sensing more significant. One of the most interesting challenges in the ground of hyperspectral image processing is unmixing. Identifying of the endmembers is based on finding the pure pixels in the understudy scene and then comparing the spectral profile of them to reference spectral profiles (i.e. spectral library or field data). A great number of researches have been conducted to improve preprocessing and processing algorithms in this arena. Many researchers have tried to achieve realistic results by finding a reliable method for spectral matching (e.g. Spectral Feature Fitting (SFF), Spectral Angle Mapper (SAM)) that Tetracorder algorithm is referred as most robust one.
This study aims to present a comprehensive algorithm to estimate mineral compositions of the endmembers by comparing their spectral profiles to reference spectra. This comparison is performed using by SAM, the least squares method, and area differences between unknown and reference spectra absorption features (AF). Considering that some minerals spectra do not have explicit absorption features, the answer of the algorithm is two folds; one or more minerals will be suggested according to the absorption features on and another mineral regarding to the continuum shape of the unknown spectrum.

1. INTRODUCTION

Determination of a mineralization, identification of an anomaly, and finally feasibility study of the deposit are usually expensive and time consuming. The exploration operation is conducted step by step and according to various factors like genesis of deposit, lithology of the study area, morphology, available facilities and laboratories, and probability results of past activities includes a diversity of techniques. An exploration project is generally started by rationally fast and cheap studies and continued toward precise and of course expensive activities like bore holes drilling and tunnelling.
Mineral deposit exploration has highest risk in comparison to other industrial activities. Collecting and interpretation of any available information is therefore crucial before stepping on deep drilling stage. Remote sensing methods are one of the helpful techniques for this purpose. They are faster and cheaper than other prospecting methods. Developing of image processing methods for hyperspectral data on the other hand has made remote sensing more significant. One of the most interesting challenges in the ground of hyperspectral image processing is unmixing. This is performed by determination of the number and characteristics of endmembers and unmixing computations. Identifying of the endmembers is based on finding the pure pixels in the understudy scene and then comparing the spectral profile of them to reference spectral profiles (i.e. spectral library or field data). A great number of researches have been conducted to improve preprocessing and processing algorithms in this arena. The investigations performed by researchers like Crosta and Filhu (2000), Cudahy et al. (2000), Kazok and Duke (2000), Kruse and Boardman (2000), Lévesque et al. (2001), Lennon et al. (2001), Bierwirth et al. (2002), Botchko et al. (2003), Wang and Chang (2006), Du et al. (2006), Oskouei and Busch (2008), and Oskouei (2010) are of the related examples which reflect challenges and implementations in the field of hyperspectral mineral detection during last decade.
Many researchers have tried to achieve realistic results by finding a reliable method for spectral matching (e.g. Spectral Feature Fitting (SFF), Spectral Angle Mapper (SAM)) that Tetracorder algorithm is referred as most robust one (Clark et al. 2003, Ong et al. 2003).
According to Clark et al. (2003), the Tetracorder method, makes a comparison between unknown spectral profile (endmember) and reference profiles (expert system). No match will be the answer if there is not

significant similarity between them. The reference spectra include all possible surfaces (e.g. minerals, vegetation types, manmade, etc). The endmembers types inside the study scene on the other hand are usually limited due to the study scope. Therefore, the prior information about the possible surface types will decrease the number of the reference spectra that must be checked. For example, if it is known that the endmembers are rock outcrops, matching the endmember only to the rocks or minerals spectra will yield more accurate results. In the same way, if it is already known that this outcrop is an intrusive, it will reasonably be matched only to the spectral profiles of igneous rocks. This will decrease the possible detection error while is not considered in Tetracorder. In an investigation of mineralogy of a terrain, therefore, prior information about geological structures, genesis, and tectonic of understudy area will have a priceless role. The presented program in this research is designed for mineral detection and the comparison is then limited to only minerals spectra.

Finding pure pixels which are consisted of solely one main mineral inside an image is usually impossible, and the purest pixels in the images are not pure in fact. Another advantage of this program is that the endmember spectrum is not considered to be a pure pixel and hence there is an opportunity to decide about the number of minerals included in a spectral profile of an endmember according to the absorption features. Consideration of above mentioned topics gives a significant advantage to the presented algorithm that will be discussed here.

SPECTRAL PROFILES

Every material on or off the earth's surface reflects electromagnetic wave in a characteristic pattern; the manner in which light of different wavelengths is reflected from or absorbed by each material is known as its reflectance spectrum. By filtering reflected light to specific wavelengths of the electromagnetic spectrum (or colour for the visible part of the spectrum) images can be created that enhance our ability to differentiate materials (Adler et al. 1999)

In the case of mineral detection, the variety of absorption processes, their wavelength dependence, sometimes the overall shape of profiles' continuums, and mean reflectance intensity allows us to derive information about the chemistry of a mineral from its reflected or emitted light. Therefore, the helpful parameters in the detection procedure are followings:

1. Absorption features (their shape and related wavelength)
2. Overall shape of profiles' continuums
3. Intensity of reflectance

The first one is most important for identifying of mineralogy of the study scene because it is indicative for chemical composition. The shape and location of absorption features on a spectrum is known as minerals fingerprints (alunite profile in figure 1). Some minerals on the other hand don't have distinct absorption features and therefore this measure is not able to detect them in an unknown spectrum. In this case, investigation of overall shape of their profile continuum will be useful. The albite spectrum in the figure 1 is an example that illuminates the detection problem specially when unknown is a mixed spectrum. The third parameter, intensity of reflectance, is not helpful for mineral detection in the process of real hyperspectral data since it is directly depended on the intensity of incident energy which is variable regarding to data acquisition time.

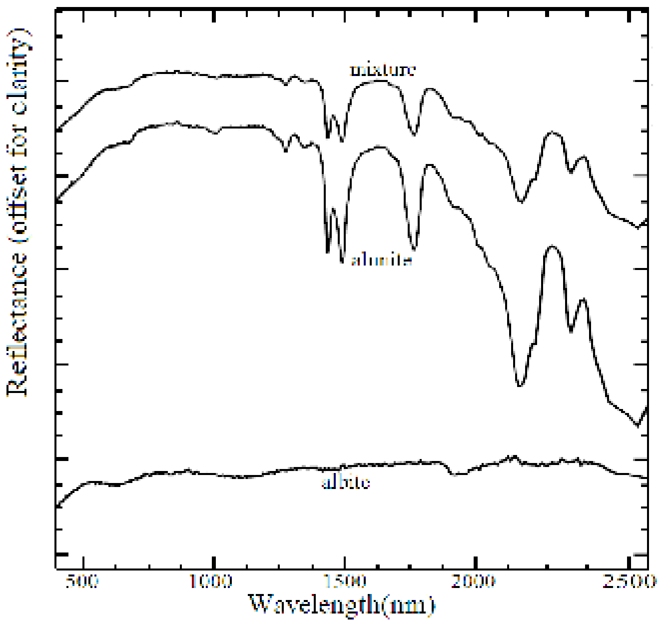

Figure 1: spectral profiles of albite, alunite, and their 50% mixture

2. METHODOLOGY

This algorithm is designed solely for mineral detection and therefore it is applicable only to lithology and soil constituent studies. Since the reference spectra in this algorithm include only the minerals spectrums, the results will be more practical in the geological terrains. The method is implemented in two stages, preprocessing and determination of the unknown spectrum. In the Hyperspectral image analysis, distinguishing of the minerals constituents of a pixel is done with the use of its spectral profile. Reliable and accurate results will be achieved if the distortions on the image are correctly rectified. These corrections are generally including topographic and atmospheric corrections, and some other preprocessing algorithms respected to the technical characteristic of sensors and data for instance, smile effect correction and polishing for Hyperion data (Oskouei and Busch, 2008). In addition to that, the reference mineral spectral library must be resampled regarding to the wavelengths of data bands as the reference spectra are collected usually by high spectral resolution spectrometers.
Since all minerals do not have explicit absorption features on their spectral profiles, in the current study, two libraries were formed consisting of minerals with and without absorption features. The unknown spectrum will then be compared to the spectra in both libraries and the best matches from the libraries will be identified.
As discussed in previous section the number of the answered minerals for each unknown spectral profile by the algorithm is directly depended on the number of absorption features.

Minerals are categorized in two groups, with and without exact absorption features. As mentioned earlier, the unknown spectral profile which is to be determined, usually is a mixture of a few minerals. For example figure 1 illustrates the spectral profiles of alunite and albite and their 50 percent mixture.
The mixture profile is closely similar to alunite profile, however, 50 percent of that belongs to albite and only a small change in continuum of mixture profile is detectible. Therefore, minerals without exact absorption features are always in a shadow and they need treated separately. The majority of previous attempts in this arena have ignored this point but in this study we survey them by different approaches and will be discussed below.

ALGORITHM DESCRIPTION

In this method, the comparison between reference spectra and unknown spectrum will be done with the use of SAM, the area of absorption features, and least squares (LS). This comparison is performed in the whole range of data wavelength or in the SWIR range determined by the user. The answer of the algorithm is based on the total scores of the three comparison methods and in two parts. One or more minerals will be estimated from the spectral library of the minerals with exact absorption features and another one from the spectral library of the minerals without exact absorption features. The number of the resultant minerals is directly depended on the number of absorption features on the unknown spectrum.

SPECTRAL ANGLE MAPPER

This was selected due to its better performance than other classification algorithms (Shafri et al., 2007, Park et al., 2007). The SAM algorithm is a tool for rapid mapping of the spectral similarity of image spectra to reference spectra. This simple classification tool is often used as a first approach to the hyperspectral data and reliable when images have brightness shifts and other spectral artifacts present compare to other classification algorithms. The SAM is a physically based spectral classification that uses an n-dimensional angle to match pixels to reference spectra. This method determines the spectral similarity by calculating the angle between the spectra, treating them as vectors in a space with dimensionality equal to the number of bands or wavelengths. The angle between the endmember spectrum vector and each pixel vector in n-dimensional space is compared. Smaller angles represent closer matches to the reference spectrum. Pixels further away than the specified maximum angle threshold in radians are not classified. This method is relatively insensitive to illumination effects. In this study, the reference spectra were extracted from region of interest (ROI) hypercube data. The lines connecting each spectrum points (a and b) and the origin contain all possible positions for the sample, corresponding possibly intensity changes due to the illumination variability (Figure 2). However, the angle (α) between two vectors is independent of their lengths. The angle between testing spectrum vector a, and reference spectrum vector b, can be calculated by the following equation (Park et al. 2007):

$$\alpha = cos^{-1}\left(\frac{\vec{a}.\vec{b}}{\|\vec{a}\|.\|\vec{b}\|}\right)$$

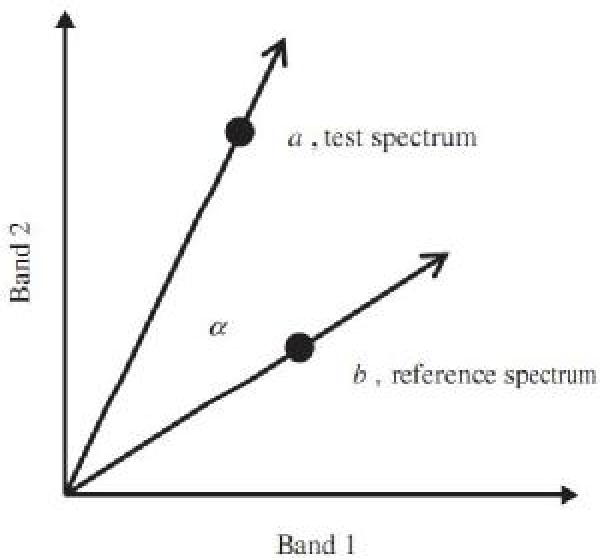

Figure 2: the angle between the vector representations of the spectrums (Park et al. 2007)

LEAST SQUARES METHOD

This part of the algorithm easily computes the square root of differences between unknown spectral profiles and reference spectra. Each spectrum of the reference profiles will have a score according to calculated square root that score is smaller for higher differences.

Area score

This method aims to quantify the similarity of the shape of coinciding absorption features on the both unknown and reference spectra. The important parameter in this computation is depth of an absorption feature in both comparing spectral profiles. In this study, however, the area of triangle (representing both width and depth) of absorption feature is considered. Differences between the calculated area for a certain absorption feature on unknown and known spectrums will be another criterion for overall similarity of spectral profiles.

THE ALGORITHM PROCEDURE

The presented method requires performing necessary preprocessings to achieve optimum estimations. They are atmospheric and topographic corrections, rasampling library spectra according to unknown spectrum wavelength, and any other possible corrections regarding to the specifications of the selected sensor. The main steps of the algorithm are briefly listed below. In the following description, L_{wi} and L_{wo} refer to the spectral library of minerals with and without absorption features respectively.

1. Inputs the unknown spectrum and libraries
2. Removes continuum of them
3. Finds the absorption features (AFs) location on unknown
4. Computes the area of AFs
5. Computes the area of AFs on L_{wi} spectrums that occur in the same wavelength of the unknown AFs
6. Calculates the area score
7. Computes the SAM score
8. Calculates least squares score
9. Scales all the scores in the same range (0.0 - 1.0)
10. Calculates total score (summing the above scores)
11. Presents one or more mineral having highest total score
12. Computes the least squares root between unknown and L_{wo} spectrums
13. Presents one or more mineral having lowest square roots

3. DISCUSSION

Determination of mineralogy of the detected endmembers is a main goal of the processing of hyperspectral data. The matching algorithms for this purpose usually ignore the essential difference between minerals with and without absorption features. As discussed in the text, the minerals without AF are generally in a shadow and their detection is difficult. The presented algorithm aimed to survey the two groups separately and therefore is able to find the minerals without AF better than previously used methods. The initial results from test data were satisfactory; however, it needs more practical works on real data to establish the real capability of the method. The algorithm is dynamic so any new matching method in the community may be added to the overall procedure of the method.

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