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The recognition of altered rock based on spectral modeling and matching using hyperspectral data

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Purpose:

Remote sensing especially hyperspectral remote sensing has contributed significantly to mineral exploration and alteration detection[1,2], such as the recognition of the hydrothermally altered rocks based on their spectral characteristics.

In this paper, we focused on the alunite alteration which was characteristic of hydrothermal alteration zones in the study area of Cuprite mining area in southwestern of Nevada[3,4]. Two solutions were practiced to improve the alteration recognition precision and reliability. One is the modeling of object reflectance spectrum with the combination of linear and nonlinear model, which was taken as reference spectrum instead of the mineral spectrum from spectral library, another is the fusion of the information extraction methods including spectral characteristic analysis and spectral matching by the weights decision function. Several rule images were obtained in which each pixel representing the similarity between the corresponding pixel in the hyperspectral image to a reference spectra (altered rock spectra). An alteration map with improved precision was created after weights decision processing. The hyperspectral data used in the paper was collected by Airborne Visible/InfraRed Imaging Spectrometer (AVIRIS) in June 19 in 1997.

Methods and result:

Three important steps in the total method of the altered rock recognition were: (1)modeling of object reference reflectance spectrum, (2) spectral characteristic analysis and spectral matching, (3) decision with weights function.

The modeling of reference spectrum was realized by the spectral mixture model which was brought forward for hyperspectral image. In the spectral mixture model, endmembers were divided into two level, one was microcosmic level and another was macroscopical level.

The nonlinear mixture is considered in the microcosmic level because the mixture is intimate, for example, the rock reflectance is a nonlinear combination of the reflectance of minerals. Linear mixture in macroscopical level is considered because the mixture can be taken as areal mixture, for example the pixel reflectance is a linear combination of components which are contained in the pixel. The alunite altered rock spectrum was calculated by this spectral mixture model. At first, the spectrum of alunite altered rock was calculated by the nonlinear spectral mixture model of Hapke[5,6,7] and Shkuratov[8], the four endmember minerals were alunite, kaolinite, opal and limotite with percent of 80%,5%,10%,5% respectively, then the object spectra was obtained by the linear combination of the spectrum of the alunite altered rock got in the former step and the vegetation Saltbrush with the percent of 95% and 5%. The modeling spectrum of alunite altered rock is similar to the image endmember spectra extracted by endmember selection method SMACC in ENVI software.

The spectral characteristic analysis was mainly to get the absorption feature parameters .The absorption parameters including:(1)absorption position, (2)absorption depth, (3)absorption width, (4)symmetry[1]. The most valuable parameters were absorption position and absorption depth. The parameterization of spectral absorption features is based on the continuum remove of the reflectance spectrum.

The aim of spectral matching is to get rule images which presenting the similarity between the pixel spectrum and reference spectrum. The matching method contains spectral angle matching (SAM), spectral correlation matching (SCM) and spectral feature fitting (SFF). SAM is a pixel based supervised classification method that measures the similarity of an image pixel reflectance spectrum to a reference spectrum in which the measure of similarity is the spectral angle between the two spectra[9]. The SCM algorithm is a spectral classifier measuring similarity between the two spectra by Pearsonian correlation coefficient[10]. SFF matches the image pixel reflectance spectrum to reference spectrum by examining specific absorption features in the spectrum after continuum removal has been applied to both the image and reference spectra[11].

After the processing of spectral characteristic analysis and spectral matching, several index rule images can be get which presenting the similarity between the pixel spectrum and reference spectrum. These rule images presented the content of the object and were the bases for decision.

The purpose of decision with weight function is to identify the altered rock in the image[11]. Three types of weight function were used in the paper: (1) binary weights function, indicating whether a pixel has a high probability of alunite being present or not; (2) scaled weights function, indicating the degree of a pixel's probability of being classified as reference object(alunite altered rock) and also indicating the abundance of object.(3) integrated weights function, it is based on several index rule images to indicate the probability or abundance of the object（alunite altered rock）, the index rule image contained absorption index image, SAM rule image, SCM rule image and SFF rule image. The key and difficult point in this part is the selection of thresholds for each index rule image.

Conclusions:

The study resulted into two main conclusions:

(1) the spectral mixture model brought forward in this paper integrated the linear and nonlinear mixture and provided an available and useful method for reference spectral modeling of objects. The alunite altered rock recognition based on the modeling spectrum performed better than just based on the spectrum in library.

(2) the weights function integrated several information extraction methods such as SAM, SCM, SFF, so the alunite altered rock recognition precision and reliability based on weights function decision is more reliable and robust, its result is better than any single method.

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