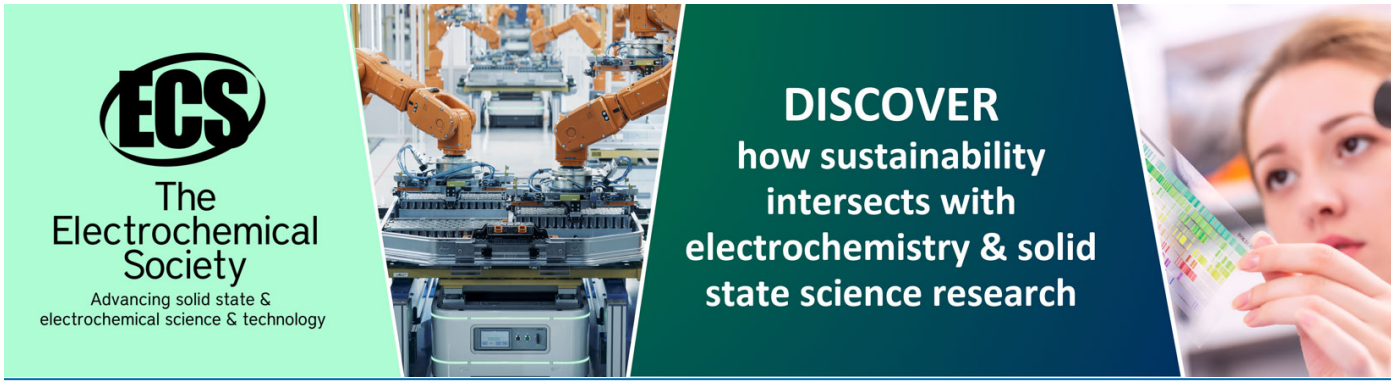
A Method to Improve Mineral Identification Accuracy Based on Hyperspectral Data



A Method to Improve Mineral Identification Accuracy Based on Hyperspectral Data

Y J Wang [1,2], Q Z Lin [1] ,Q J Wang[1], Y Chen[1]

[1] Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing, 100094, China

[2] University of Chinese Academy of Sciences, Beijing, China

E-mail: tangshanwangyj@163.com

Abstract. To improve the mineral identification accuracy of the rapid quantificational identification model, the noise was filtered in fragment based on the wavelength of altered mineral absorption peak and the regional spectral library that fitted for the study area was established. The filtered spectra were analyzed by the method with regional spectral library. Compared with the originally mineral identification result, the average efficiency rate was improved by 5.1%; the average accuracy rate was improved by 17.7%. The results were optimized by the method based on the position of the altered mineral absorption peak. The average efficiency rate would be improved in the future to identify more accurate minerals.

1. Introduction

Varieties of minerals and their content are integrant to process mineral mapping by hyperspectral technique. While mineral identification methods are still remaining at traditional stage as telescope identification [1], X-Ray Diffraction [2] and electronic probe [3]. With complex sample treatments and high cost, traditional methods cannot meet the demand of scientific developments as being quick and economical. In the application of remote sensing technology and hyperspectral technology, the analysis of rocks and minerals have superiority to traditional ways. So it is necessary to establish a quantitative method of mineral compositions based on remote sensing to be adapted for the developmnet of the research on environment and mineral sources remote sensing.

Nowadays, using near infrared spectra of rocks to identify minerals is available with the development of spectral technology. Hyperspectral methods for mineral alteration information identification and extraction mainly include spectrum waveform parameters, spectral similarity measure and spectral mixing model [4]. Shuai LI has presented a promising quantificational identification model of minerals to acquire the mineral category and content in rock samples by analyzing mineral spectra of visible and near-infrared bands [5]. This research aims at building a spectral library, preprocessing the spectra and optimizing results to improve mineral identification accuracy of the model.

2. Brief introduction of quantificational identification model of minerals

At present，the spectral characteristics of minerals have been detected at visible and near-infrared bands[6]. Including absorption peak wavelength, absorption depth, symmetry and peak width,

absorption characteristics of mineral spectra and the shape envelope curves are functions of mineral component and abundance, which is the starting point of mineral identification. A spectrum of a rock sample at near-infrared band is regarded as a curve and the absorption peaks can present the component of every end number spectrum. Each absorption peak is regarded as a triangle, which is controlled by three points（left shoulder, right shoulder and the acme）. Each point is the linear superposition result of mineral spectrum component, which can be analyzed by math method to get the exact result. The standard procedure is shown in Figure 1.

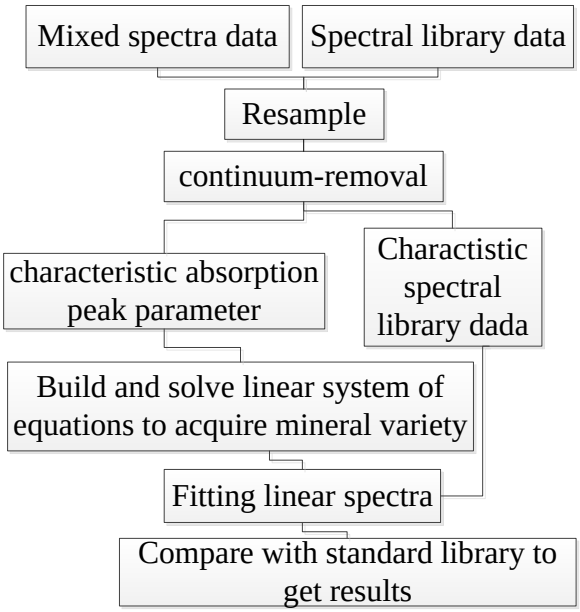


Figure 1. Mineral component extraction model flow chart

3. Improvement for the accuracy of mineral identification model

3.1. Influence factor to the mineral identification accuracy

Besides the complexity of the spectra, there are several factors to influence the accuracy. First one is how to select spectral library. Mineral component of rock sample, which is closely related to geological environment of sampling point, must obey basic geological principle. The default spectral library used in this model is USGS spectral library, which contains almost all kinds of mineral spectra. Using this library as the standard to analyze the mineral component may lead to wrong results and poor efficiency. The second one is the spectrum noise. There are random noises in the spectra measured by ASD spectrometer, which will influence the model to identify absorption peaks. The third one is that the matching method in this model also can have an impact.

3.2. Methods to improve the accuracy

Aiming at these questions, three methods have been presented to improve the accuracy.

3.2.1. Standard spectral library for research area is established. Mineral association is related to the local geology background, so detailed survey for geology information of sampling point is necessary. According to mineralogy and mineral paragenetic relationship, major mineral species and alteration combination in the region are summarized. Possible minerals in the sampling area are retained in USGS spectral library to establish the standard spectral library and the impossible ones are eliminated.

3.2.2. Method of filtering preprocessing for rock spectra is presented. By researching mineral species of the sampling area, the positions of mineral absorption peaks are summarized, which mostly focus

on near-infrared bands. Near-infrared bands are divided into two parts, absorption peak compact district and noise compact district. Noises are filtered at noise compact district.

3.2.3. Optimizing method for results of mineral identification is presented.
A Remove continuum of the mineral spectra, and extract the absorption peak positions.
B Summarize absorption peak positions of the sample spectra and standard spectra.
C Seek out mineral associations of the same position after comparing sample spectra and standard spectra.
D Compare the results from C with non-optimized identification results to screen the best.
E Compare fitting spectra of the optimized identification results with sample spectra to ensure the accuracy.

4. Applications of the improved method

4.1. Data acquisition and technical route

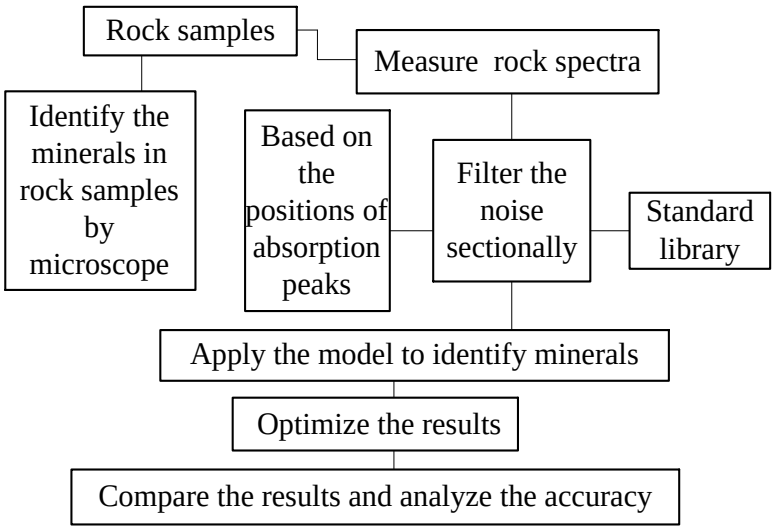


Figure 2. The optimized mineral identification accuracy contrast flow chart

Twenty samples analyzed in this article were derived from Sinkiang Baogutu rock body V. Rocks in body V are mainly granodiorite and granodiorite-porphyry, composed of quartz, plagioclase, black mica, amphibole and some potassium feldspar [7]. Metallogenic type of rock body V is typical porphyry copper with inside-out alteration zonal distribution of K feldspathization, quartzsericitization and propylitization. 20 rock samples were cut into slices to identify mineral constituent with microscope.
The results are regarded as standard to check the results of mineral identification model. Then the samples were grinded into powder to measure spectra by ASD spectrograph. Technical route is shown in Figure 2.

4.2. Data processing

4.2.1. Establishment of research area spectral library. By researching literature and field studying, main minerals in rock body V were summarized including feldspar, quartz, biotite, augite, hornblende, rutile, apatite, sphene, sericite, kaolinite, illite, chlorite, Chalcopyrite，pyrite, magnetite, hematite and red copper ore[8,9]. Paragenetic minerals then were added through paragenetic relationship in mineralogy. Spectra from USGS library of all the selected minerals were gathered to save as standard library.

4.2.2. Sectional preprocessing of spectra. Filtering, like Fourier filtering and wavelet transform, is mainly to filter the zero mean high frequency spectrum of random white noise. Qing-jie LIU has presented continuum based fast Fourier processing method with fine effect [10]. Main concept of CFFT shows in the following. First, remove continuum of the spectra to be processing. Then separate noise from the signal by fast Fourier transform. After that, design low pass filter to filter high frequency white noise. At last, regain spectral signal on the basis of spectral continuum.

By researching of mineral spectra, absorption peak position of propylitization appears at wave length 2335nm, quartzsericitization and K feldspathization appear at 2250nm, clayization appears at 2205nm and carbonatation appears at 2350nm. In conclusion, noises at 2000~2200nm，2250~2300nm，2350~2500nm were filtered and detail information at 2200~2250nm，2300~2350nm was remained to save as filtered spectra. Filtering effect is shown in Figure 3.

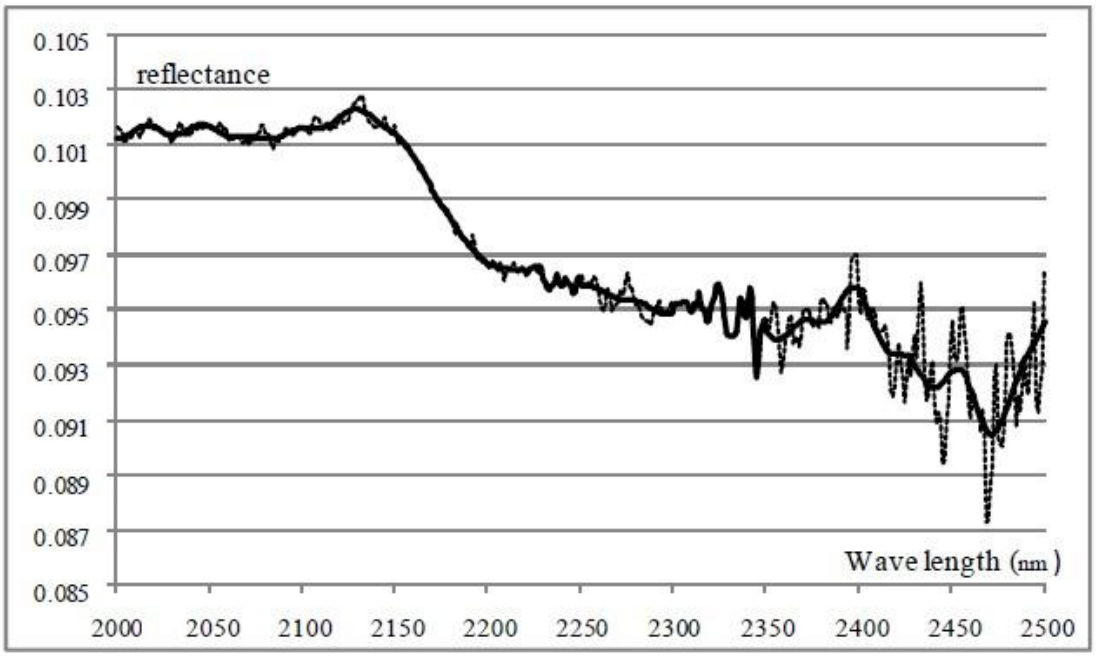


Figure 3. Comparison chart about original spectrum and filtered spectrum, Full line stands for filtered spectrum and dotted line stands for original spectrum

*4.2.3. Applying of processing model.*Mineral identification model was applied to analyze the filtered spectra by comparing with standard library to get results. Then optimizing was processed.

4.3. Precision analysis of results

Comparison of the results between original model and improved model shows in table 1.C represents actual component of minerals, Y represents number of all minerals extracted by original model, m represents correct number of original model, T represents all minerals extracted by improved model, n presents correct number of improved model, E represents all minerals after optimizing.

Accuracy of identification has been improved obviously after filtering and applying standard library. Average accuracy (accuracy=correct number of mineral kinds exacted by the model/ all the minerals exacted by the model) after filtering is 48.7% by rising 17.7%. Average effective rate (effective rate= correct number of mineral kinds exacted by the model/ minerals identified by microscope) after filtering is 62% by rising 5.1%. Through table 1, the advantage of optimizing method is obvious.

Table 1. Mineral identification results comparison table of different methods

No.	C	Y	m	T	n	E	Improved model		Original model	
							effective rate (n/C)	accuracy (n/T)	effective rate (m/C)	accuracy (m/Y)
3	10	10	4	12	7	11	70%	58.30%	40%	40.00%
4	11	11	4	8	5	7	45.50%	62.50%	36.40%	36.40%
5	10	5	2	6	4	6	40%	67%	20%	40.00%
7	10	38	1	19	8	16	80%	42%	10%	2.60%
2319	11	24	5	19	6	14	54.50%	31.50%	72.70%	20.80%
2330	9	33	7	15	7	14	78%	47%	77.80%	21.20%
2354	8	34	7	17	6	12	75%	35%	87.50%	20.60%
2355	10	8	4	7	4	7	40%	57%	40%	50.00%
2356	9	38	9	12	5	11	56%	42%	100%	23.70%
2360	8	5	1	10	4	10	50%	40%	12.50%	20.00%
2361	11	30	6	16	8	13	72.70%	50%	54.50%	20.00%
2367	4	22	2	5	3	5	75%	60%	50%	9.10%
A	9	26	7	13	7	11	77.80%	54%	77.80%	26.90%
B1-14	9	11	4	10	5	10	55.60%	50%	44.40%	36.40%
B2-7	10	10	5	14	6	13	60%	43%	50%	50.00%
B2-12	12	20	8	16	7	14	58.30%	44%	66.70%	40.00%
B2-42	9	12	5	12	6	12	67%	50%	55.60%	41.70%
B5-5	8	12	5	17	6	14	75%	35%	62.50%	41.70%
B5-17	10	15	5	9	6	8	60%	67%	50%	33.30%
BW-1	10	15	6	13	5	12	50%	38%	60%	40.00%
average							62%	48.70%	56.90%	31.00%

5. Conclusion and prospect

In this article, noise filtering and standard spectral library are presented to successfully improve accuracy and effective rate of mineral identification model. Optimizing method based on absorption peak positions of mineral spectra is established. This method contributes to extract mineral category correctly by reducing superfluous minerals.

The improvement for mineral identification model was only tested by 20 samples from rock body V, Baogutu. So applicability needs to be ensured by more samples. So more detail work should be done in the future to complete the model.

Acknowledgments

This research was financially supported by National Natural Science Foundation of China (No. 41171280), the National Science and Technology Support Program (No. 2012BAH27B05), and project remote sensing recognition on typical porphyry body based on spatial-spectral object supported by Director Foundation of CEODE, CAS.

References

[1] Wang D Z, Xie L 2008 *Optical Mineralogy (The third Edition)* (Beijing, Science Press)

[2] Jin Y, Sun X S, Xue Q 2008 *X-Ray Diffraction Analysis Technology* (Beijing, National Defense Industry Press)
[3] Lin T H, Zhang J G 1980 *Electron Microprobe Analysis* (Beijing, National Defense Industry Press)
[4] Gan F P, Wang R S, Ma A N 2003 *Earth Science Frontiers* **10** 445
[5] Li S, LIN Q Z 2010 *Spectroscopy and Spectral Analysis* **30** 1315-1319
[6] Yan S X, Zhang B 2003 *Remote sensing technology and application* **18** 191-201
[7] Dai H W, Shen P 2010 *XinJiang Geology* **04** 440-447
[8] Song H X, Liu Y L 2007 *Acta Petrologica Sinica* **23** 1981-1988
[9] Cheng Y, Zhang R 2006 *Western Jungar, Xinjiang* **42** 11-15
[10] Liu Q J, Lin Q Z. 2009 *Spectroscopy and Spectral Analysis* **29** 3279-3282