Field Hyperspectral Remote Sensing of Target Region in Xiemisitai Mountain, Xinjiang Province, China.

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Abstract. A fine mineral identification model using the field Hyperspectral remote sensing was proposed to solve the problem of low mineral identification accuracy. Results show that the accuracy was improved by spectral noises removal, endmember optimization and mineral absorptions enhancement. A regional endmember library was established to improve the reliability by systematically considering of the mineral assemblage relationships. A fine mineral identification system (FMIS) was developed to help geologists to quickly identify minerals and it was applied in the Xiemisitai Mountain, Xinjiang province, China in 2014 to newly find copper mineralized points. The improved model and the FMIS system are therefore not only of great significance to improve efficiency and save cost in remote sensing mineral exploration, but also of great economic value of the local economy development in the future.

1. Introduction

Minerals, the basic unit of rocks, are stable elements or compounds under certain geological and geophysical conditions during the multi-period geological activities. Primary minerals in rocks are called rock-forming minerals, while those with changed components or structures are named as the alteration minerals. Rock-forming minerals, such as quartz, feldspar and mica, are primarily silicates, carbonates and oxides. Alteration minerals are primarily the components in hydrothermal mineralization, which are important indicators for mineral prospection. The common alteration minerals include skarnization, greisenization, sericitization and propylitization, etc. There are many techniques to determine mineral contents in laboratory, such as the slice identification, X-Ray diffraction analysis and the electron probe detection. However, large-scale field mineral identification needs a fine mineral identification model using the hyperspectral remote sensing to quickly map minerals.

Mineral inversion models, such as the linear spectral unmixing and the nonlinear spectral unmixing models (Hapke B 1981; Shkuratov Y et al. 1999) have been proposed. Classic techniques
for mineral identification and rock info enhancement, such as the spectral angle mapper (Kruse F A 1993), Principle Component Analysis (Singh A and Harrison A 1985), Maximum Noises Fraction transformation (MNF) (Green A A etal. 1988) and Crosta transformation (Crosta A P and Moore J M 1989) have been established. Recently, new methods, such as spectral energy level matching (Wang Q J and Lin Q Z 2006a, Wang Q J et al. 2007), weighted spectral angle mapper (He Z H and He B B 2011; Liu K et al 2013), derivative of ratio spectroscopy (Zhao H Q et al 2013), rapid mineral quantification identification model (Li S et al 2010), improved ICA algorithm (Wu F H et al. 2013), generalized morphology-based hyperspectral image unmixing algorithm (Zhao Y et al 2015) were proposed to explore golds (Safwat G et al 2010; Ren G L et al 2013), coppers (Wang Q J and Lin Q Z 2006b; Yusuf E M et al. 2014), boron (Bernard E H and James K C 2005), geothermal deposits (Vaughan R G et al 2005; Christopher K et al 2010), martian components (Frank J AV et al 2014), oil deposits (Chen S B et al 2012) and the volcanic evolution activities (Brandmeier M et al. 2013).

2. Regional settings
As shown in figure 1., with a low hilly area in relief, the study area is located in the Xiemi	isaitai Mountain, which is 25km southwest to the Hoboksar County, Tacheng district, Xinjiang province, China. Hebuke River passes through the county and becomes a primary water source for the Hoboksar town. With an average temperature of 3°C and precipitation of 142mm, it is a continental arid climate, which is characterized by long winter, short summer, windiness in Spring and autumn.

As shown in figure 2., strata in this area are primarily in the Erjisite group developed in the middle Devonian with intermediate-arid intrusive rocks, volcanic tuff and agglomerate. Rocks of the strata are primarily the light gray andesite, dacite, rhyolitic brecciated crystal tuff. Composed of the meat-red potassium granite, the deeply intrusive rocks are distributed in the northern and western. However, the shallow intrusive rocks are primarily located in the southwest and southeast, which are primarily composed of the light meat-red granite porphyry, gray altered andesitic porphyrite and the purple andesite.

Structures of the study area are primarily the NE and near EW faults. They are primarily straight valleys with 3-10m width, 2-7m depth and 2-4km long.

The surface alterations are primarily epidotizations, carbonations and malachites. The malachites are primarily developed in the andesitic porphyrites in the eastern, especially obvious in the intersections of two fault groups with orientations of 20-30° and 110-120°.

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**Figure 1. Location of the study area.**
3. Method

A fine mineral identification model is established taken the measured spectra as the data resource, which were measured by the Analytical System Devices, Inc. portable field spectrometer (ASD FieldSpec®3). In which, a regional spectral library and those methods smoothing spectra and optimizing endmember selections are developed to improve the mineral identification accuracy.

3.1. Principles

In nature, especially in the process of mixed spectral analysis of rock and mineral compositions, the mixed pixels are commonly existed. The linear spectral mixture is considered as the primary mixed model (Zhao H Q et al. 2013; Wang Y J et al. 2012). It is a linear equation expressing the correlation between the mixed pixel spectra and the endmembers spectra, whose hypothesis is that a pixel spectrum is linearly composed of multiple endmembers, written by:

\[ B = AX + \varepsilon \]

In which, \( A \) is a \( n \times n \) array, representing \( n \) endmember spectra with \( n \) bands; \( X \) is a \( n \times 1 \) array, representing the endmembers weights that should be determined by the equation; \( \varepsilon \) is the residual; \( B \) is a \( n \times 1 \) array representing the measured spectrum with \( n \) bands in a pixel. The mathematic expression of the model can then be concluded to find an optimized solution of \( X \) to minimize the residual using the least squares method.

In order to solve the problem, spectral processing, including endmember selections and noises removal, becomes necessary. Therefore, a regional endmember library and a spectral noises removal method using the Fourier transformation become the innovation of the model.
According to above principles, a Finely Mineral Identification System (FMIS) V1.0 was developed using C++BuilderV6.0 software.

3.2. Precision evaluation.
As shown in table 1., according to the slice identified minerals in the laboratory, a regional endmember library was established by selecting the standard spectra from the USGS mineral library. Using the mineral contents and their standard spectra, the simulated spectra are reconstructed by the linear spectral mixture model.

| Sample | Spectral No. | Mineral contents (%) |
|--------|--------------|----------------------|
| 4      | 020-024      | Plagioclase, 45%; Quartz, 30%; Hornblende, 20%; Calcite, 3%; Chalcopyrite, 1%; Limonite, 1% |
| B-5-5  | 025-029      | Orthoclase, 70%; Plagioclase, 20%; Quartz, 5%; Biotite, 2%; Pyroxene, 2% |
| 5      | 030-034      | Pyroxene, 70%; Plagioclase, 20%; Potassium feldspar, 10% |
| B-2-12 | 035-039      | Plagioclase, 60%; Hornblende, 15%; Pyroxene, 10%; Biotite, 5%; Quartz, 5%; Sphene, 2%; Magnetite, 1% |
| BW-1   | 045-049      | Potassium, 65%; Plagioclase, 15%; Hornblende, 10%; Biotite, 5%; Sphene, 1% |
| B-5-17 | 050-054      | Orthoclase, 65%; Plagioclase, 10%; Hornblende, 15%; Biotite, 5%; Pyroxene, 2% |
| 2319   | 055-059      | Orthoclase, 40%; Plagioclase, 35%; Quartz, 10%; Hornblende, 5%; Biotite, 5%; Pyroxene, 3%; Sphene, 5% |
| 7      | 060-064      | Quartz, 25%; Plagioclase, 40%; Potassium feldspar, 20%; Hornblende, 15% |
| 3      | 065-069      | Plagioclase, 60%; Hornblende, 20%; Quartz, 10%; Chlorite, 10% |
| A      | 070-074      | Quartz, 30%; Potassium feldspar, 45%; Plagioclase, 20%; Hornblende, 5% |
| 2361   | 075-079      | Plagioclase, 70%; Hornblende, 15%; Quartz, 5%; Biotite, 3%; Pyroxene, 2%; Magnetite, 3%; Ilmenite, 2% |
| B-1-14 | 080-084      | Plagioclase, 70%; Hornblende, 20%; Biotite, 5%; Quartz, 3%; Pyroxene, 2% |
| 2360   | 085-089      | Plagioclase, 60%; Pyroxene, 30%; Biotite, 5%; Hornblende, 5%; Magnetite, 1% |
| 2356   | 090-094      | Potassium, 70%; Ilmenite, 10%; Hornblende, 5%; Pyroxene, 5%; Biotite, 5%; Calcite, 1%; Hematite, 1%; Rutile, 1% |
| 2355   | 095-099      | Plagioclase, 60%; Quartz, 15%; Hornblende, 10%; Pyroxene, 10%; Biotite, 5% |
| 2354   | 101-104      | Quartz, 35%; Potassium feldspar, 50%; Albite, 10%; Hornblende, 5% |
| 2330   | 105-109      | Plagioclase, 65%; Hornblende, 20%; Quartz, 5%; Pyroxene, 5%; Magnetite, 5%; Ilmenite, 3%; Limonite, 1% |
| B-2-7  | 111-114      | Plagioclase, 60%; Hornblende, 20%; Biotite, 10%; Quartz, 5%; Pyroxene, 5% |
| B-2-42 | 115-119      | Orthoclase, 40%; Plagioclase, 35%; Biotite, 10%; Hornblende, 5%; Pyroxene, 3%; Sphene, 2%; Limonite, 1% |

As shown in table 2., accuracies with multi-endmember groups were calculated by comparing the FMIS inversed minerals with those simulated. From which, we can see that the accuracies reduced with the increasing endmembers. The averaged mineral identification accuracy was 90.79% and the averaged error of mineral contents inversion was 2.2%, when the endmember number is less than 11.

| Endmembers | Accuracy(%) | Error(%) |
|------------|-------------|----------|
| 1          | 100         | 0        |
| 2          | 100         | 0        |
| 3          | 100         | 0        |
| 4          | 100         | 0        |
| 5          | 99.1        | 0.04     |
| 6          | 85.45       | 2.57     |
| 7          | 83.24       | 3.16     |
| 8          | 82.3        | 4.72     |

Table 1. Slice identified minerals.

Table 2. Accuracies of the model under different mineral groups.
4. Data and processing

As shown in figure 3, 362 field samples distributed along 6 lines from the western to the eastern were sampled in July, 2014. Partial samples were tested by the Leica 2500 high magnification microscope. Based on the tested mineral contents, a regional endmember spectral library was established referring to the USGS standard mineral spectra. More than 1500 spectra were measured by the ASD spectrometer. Then, the spectral noises were removed and the mineral absorption parameters were determined by the FMISV1.0 software.

5. Results and discussion

As shown in figure 4, alteration minerals were mapped based on the inversed mineral contents. Results show that they were distributed in belts: from the centre to the outer, alteration minerals were potassium, silicates and propylitizations. Mineralized points were distributed near to the intersections between NW structures, propylitization belts and the silicate belts which are important indicators to delineate target areas.

As shown in table 3, the copper contents meet the industrial exploration grade. It was, therefore, delineated as a remote sensing target region, which can be further systematically evaluated by well drilling holes to determine the underground ore deposit’s location, scale and grade.
Table 3. Laboratory determined metal contents

| Analysis number | Sample number | Au  (10^-9) | Ag (10^-9) | Cu  | Pb  |
|-----------------|---------------|-------------|------------|-----|-----|
| 1--8            | TC-2-1-H1     | 4.0         | 0.239      | 87.5| 17.7|
| 1--9            | TC-2-1-H2     | 319.3       | >1         | >10000| 213.0|
| 1--10           | TC-2-1-H3     | 2.7         | 0.227      | 104.4| 25.4|
| 1--11           | TC-2-2-H1     | 6.4         | 0.258      | 294.0| 21.6|
| 1--12           | TC-2-2-H2     | 451.7       | >1         | >10000| 86.8|
| 1--13           | TC-2-2-H3     | 63.4        | >1         | 4186.3| 56.8|
| 1--14           | TC-2-3-H1     | 182.8       | >1         | >10000| 54.9|
| 1--15           | TC-2-4-H1     | 898.9       | >1         | >10000| 45.1|

6. Conclusions
(1) A fine mineral identification model was proposed to provide a technique for quantitative minerals inversion.

The accuracy of the mineral identification was improved by the noises removal, optimized endmember selection, and the mineral spectral absorptions enhancement. Results of mineral identification were more reliable by establishing a regional endmember library.

(2) The model was applied in the Xiemsitai Mountains, Xinjiang province, China, to newly find a copper mineralized point.

According to regional settings, the mineral prospecting regions were forecasted and validated to find a copper mineralization point. Metal contents show that the study area is prospective in exploring the copper deposits.

(3) Technique proposed in this paper can be widely used in remote sensing prospecting, remote sensing image processing and the weak lithological info (such as rocks, structures and alteration minerals, etc.) enhancement and it is, therefore, of great significance to improve the mineral exploration efficiency and save cost.

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