

MULTIPLE TECHNIQUES FOR LUNAR SURFACE MINERALS MAPPING USING SIMULATED DATA

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ABSTRACT

Lunar minerals mapping is one of basic aims of China's Lunar Exploration Program. The goal of this paper was to use multiple mineral mapping techniques including classification and spectral matching for lunar surface minerals mapping and choose the effective methods based on the image data which was simulated by 76 lunar samples spectra supplied by LSCC. The results indicated that Mahalanobis Distance and support vector machine performs best of the supervised classification methods. SAM is more effective than SID of the spectral matching methods. The classification capability was different for the different size samples of the same materials. The samples with obvious diagnosed spectral characteristic can be identified effectively. Those without diagnosed spectral characteristic are sensitive to the mapping method. Besides the mapping methods, there are other factors which may affect the mapping results, such as the lunar soil component, the lunar soil maturity, the particle size and the data preprocessing procedure.

Keywords—image simulation; spectral matching method, Lunar surface minerals mapping.

1. INTRODUCTION

The distribution and types of the minerals and rocks on the lunar surface is the main topic of the China's Lunar Exploration Program and it is helpful to investigate the origin and evolution of the moon. Hyperspectral remote sensing is effective to the exploration to the lunar minerals and rocks because of its fine spectral information and its dominant role in mineral identification. At present, the imaging spectroscopy has been widely used on the earth and the Mars and the mineral identification based on the imaging spectroscopy is mature, while the importance of the imaging spectroscopy to the lunar exploration has been recognized recently.

It should be studied deeply whether those successful mineral mapping methods of the earth are effective to the surface features identification or not in that spectral characteristics of the moon are evidently different with that

of the earth. These spectroscopic differences come into being from the different physical and chemical components, the different geological formation process and different surface characteristics between the moon and the earth. The goal of this paper was to use multiple mineral mapping techniques including classification and spectral matching for lunar surface minerals mapping and choose the effective methods based on the simulated image data.

2. IMAGE DATA SIMULATION

2.1. Spectral Data Description

The soil samples returned from Apollo missions include 10 highland soils from Apollo 14 and 16 landing sites, and 9 mare soils from Apollo 11, 12, 15, and 17. Lunar Soil Characterization Consortium (LSCC) generated four sample replicates for each of the 19 highland and mare soil samples according to particle size: <45 μ m, 45–20 μ m, 20–10 μ m, and <10 μ m, for a total of 76 sample replicates, and measured the spectra over the spectral range 0.3–2.6 μ m with 5 nm sampling resolution at a phase angle of 30° (Pieters and Hiroi, 2004).

2.2. Image Data Simulation

The image data was simulated based on the spectra of 76 lunar samples supplied by LSCC using ENVI software. The simulated image has 461 bands and its spectral resolution is 5nm. The image cube of simulated image is shown in Fig. 1.



Fig.1. Image cube of simulated data

3. SPECTRA CHARACTERISTICS AND THE AFFECTED FACTORS OF LUNAR SOIL

It is helpful to improve the lunar mineral mapping precision for analyzing the lunar soil spectra characteristics and its affected factors in that the producing mechanism of the lunar soil spectra is different to that of the earth.

3.1. Spectra characteristics of lunar soil

The strict physical mechanism exists in the spectral producing of everything according to the electromagnetic wave theory. The diagnostic absorption bands of the lunar surface materials in the visible-shortwave infrared region are produced by the electron transition between the transition metal ions and in the transition metal ion and it is the same with that of the earth surface materials. These electron transition include the crystal field effects, charge transfer, conduction band, color centers. Compared to the rocks and minerals of the earth, the diagnosed spectral characteristics of the lunar rocks and minerals are less and the spectra curve is simple and the spectra slope is gentle because the lunar surface rocks are lack of Fe^{3+} and water. The spectra difference between the highland samples and the mare samples is great according to the samples returned from the lunar surface.

3.2. Affected factors of lunar soil spectra

The optical characteristics of the lunar surface materials were affected by many factors such as the chemical and physical components, structure and particle size of the lunar soil, the space environment, the lunar surface temperature. These factors will affect the result in the lunar mineral information extraction.

The chemical and physical components are the most important affected factors and they determine the diagnosed features. The optical characteristics of the lunar regolith is dominantly controlled by variations in the abundance of four components: (1) high albedo, low iron minerals (largely anorthosite); (2) iron bearing silicate minerals (primarily pyroxene and olivine); (3) maturation products (complex glasses, coatings bearing nanophase metallic iron [Hapke et al., 1975; Pieters et al., 2000; Hapke, 2001]); and (4) opaque minerals (primarily ilmenite and spinel).

In contrast with the range and sophistication of research done in the other factors, much less is done in the particle size on lunar mineral mapping and identification. And in the mineral mapping project on the earth, this effect was often ignored because of the limitation of the sensor's spatial resolution and its tiny effect on the results. For the improvement of the spatial resolution and the great effect on the lunar mineral mapping, effect of particle size should be emphasized. It can be seen that the effect of the particle size to the reflectance spectra in the visual-short wave infrared is simple from fig.2 and the basic curve of the reflectance isn't changed. The effect of the particle size to the reflectance spectral is linear.

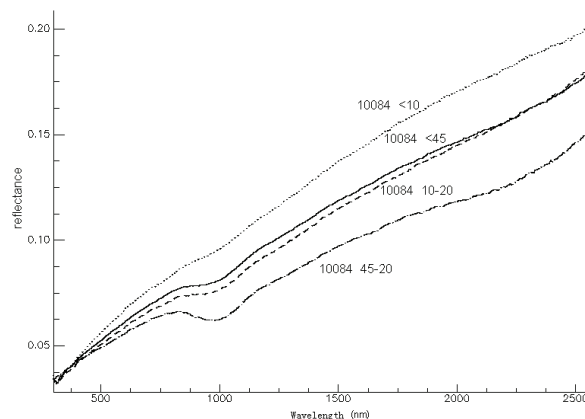


Fig.2. The reflectance of the lunar highland sample 10084 with different particle size

Another important effect to the optical features of the lunar surface materials was performed by the space environment. The effects of the space environment to the lunar soil spectra are as follows: (1) it improves the weathering of the lunar rocks; (2) it improves the particle size of the lunar soil; (3) it changes the porosity of the lunar soil; (4) it changes the chemical components of the lunar soil.

The effects of the lunar surface temperature to the lunar spectra lie in two parts. On the one hand, the diurnal variation range of the temperature is large enough to produces strong thermal shock test and it lead to the strong mechanical crush and disruption. As a result, the grain size is changed and the lunar spectral features are changed. On the other hand, the molecule vibration is affected by the lunar surface temperature; thereby the spectral features are changed.

4. CLASSIFICATION METHOD

Supervised classification technique, unsupervised classification technique, and spectral matching methods were selected to perform lunar mineral mapping.

4.1. Classification method

The results indicated that unsupervised classification was not useful to the lunar mineral mapping.

Mean values of the spectral data of four sizes ($<10\mu\text{m}$, $20\text{--}45\mu\text{m}$, $10\text{--}20\mu\text{m}$, $<45\mu\text{m}$) for every 19 samples were calculated and these mean values were chosen as training classes before the supervised classification methods were performed. The Supervised Classification methods used in this paper included Parallelepiped, Minimum Distance, Mahalanobis Distance, Maximum Likelihood, Binary Encoding, and Support Vector Machine. Different method has different results to the classification of the different sample. The results of these classification methods were shown in fig.3.



Fig.3. Supervised classification results of the simulated image

(a Training classes on the original simulated image b results of Mahalanobis Distance classification, c results of Support Vector Machine classification, d results of Minimum Distance classification, e results of Parallelepiped classification, f results of Binary Encoding classification, g results of Maximum Likelihood classification)

The ability of the supervised classification is different to the simulated image data. Mahalanobis Distance performs best and its classification precision is 100%, support vector machine is 97.37%, minimum distance, Parallelepiped, binary encoding are ordinal to 35.53%、28.95%、25%. Maximum likelihood is 11.84%.

As can be seen from the table 1, the classification capability was different for the different size samples of the same materials. Of the four sizes, the classification precision of <45 μ m sample is highest. The classification precision of 0-20 μ m sample is low than that of <45 μ m sample, The

identification precision of <10 μ m and 20-45 μ m is low comparatively.

Table 1 The classification capacity of samples with different particle size using different methods

Size	b	c	d	e	f	g	sum
<10	19/19	19/19	3/19	6/19	3/19	3/19	53/114
10-20	19/19	17/19	9/19	5/19	4/19	2/19	56/114
20-45	19/19	19/19	2/19	6/19	5/19	2/19	53/114
<45	19/19	19/19	13/19	6/19	9/19	2/19	68/114
sum	76/76	74/76	27/76	23/76	21/76	9/76	

Table 2 The classification capacity of different kinds of samples using different methods

Sample	b	c	d	e	f	g
10084	100%	100%	75%	100%	50%	0%
12001	100%	75%	25%	100%	50%	100
12030	100%	100%	25%	100%	50%	0%
14141	100%	100%	50%	75%	75%	25%
14163	100%	100%	50%	25%	25%	0%
14259	100%	75%	25%	0%	25%	0%
14260	100%	100%	25%	0%	0%	0%
15041	100%	100%	25%	0%	25%	0%
15071	100%	100%	25%	0%	0%	0%
61141	100%	100%	0%	0%	0%	0%
61221	100%	100%	75%	100%	25%	0%
62231	100%	100%	0%	0%	0%	0%
64801	100%	100%	25%	0%	50%	0%
67461	100%	100%	75%	0%	0%	0%
67481	100%	100%	25%	0%	0%	0%
70181	100%	100%	50%	0%	50%	0%
71061	100%	100%	0%	0%	50%	0%
71501	100%	100%	75%	75%	50%	100
79221	100%	100%	25%	0%	25%	0%

As can be seen from the table 2, the identification precision is different for the different surface features. Of the samples, sample 14141 and 71501 can be identified better using six different classification method in that they has obvious diagnosed spectra spectral characteristics. But the sample 62231 can be identified by the support vector machine and Mahalanobis Distance and can not be identified by the other methods in that it has not any absorption characteristics and its spectral feature is similar to the spectral feature of 64801、14163、61141。67481 has some spectral absorption feature, but its identification results is not good in that its spectral curve is similar to the 14141. To be concluded, the samples with obvious diagnosed spectral characteristic can be identified effectively. Those without diagnosed spectral characteristic are sensitive to the mapping method. Besides the mapping

methods, there are some other factors which may affect the mapping results, such as the data preprocessing procedure.

4.2. spectral matching method

SAM (Spectral Angle Mapping) and SID (Spectral Information Divergence) were used as spectral matching methods.

4.2.1 Spectral angle mapping (SAM)

The similarity is measured in Spectra Angle mapping (SAM) by calculating the included angle of the reference spectra and target spectra (Kruse F. A. et al, 1993) .The included angle (θ) is expressed by inverse cosine.

$$\theta = \cos^{-1} \frac{\sum_{i=1}^n t_i \bullet r_i}{\sqrt{\sum_{i=1}^n t_i^2 \sum_{i=1}^n r_i^2}}, \quad \theta \in \left[0, \frac{\pi}{2}\right]$$

4.2. Spectral information divergence (SID)

Spectral Information Divergence derives the spectral similarity measure between the target spectra and referenced spectra based on the differences of known characteristic probability distributions. The spectral of a pixel is regard as a random variable. The Spectral Information Divergence is defined as the sum of the relative information entropy between the target spectra and reference spectra as follows (chein-I Chang, 2000).

$$\begin{aligned} \text{SID}(x, y) &= D(x \parallel y) + D(y \parallel x) \\ D(x \parallel y) &= \sum_{l=1}^L p_l (I_l(y) - I_l(x)) = \sum_{l=1}^L p_l \log\left(\frac{p_l}{q_l}\right) \\ D(y \parallel x) &= \sum_{l=1}^L q_l (I_l(x) - I_l(y)) = \sum_{l=1}^L q_l \log\left(\frac{q_l}{p_l}\right) \end{aligned}$$

The results indicated that the sample such as 14141 and 61221 which has obvious different spectral features with other samples can be identified by SID and SAM method effectively. But for the other samples with similar spectral curves, the SID and SAM have different identification capacity. For example, the SID data of the 14259 and 12001, 14260, 15041, 15071 are the same as 0.0004 and these samples can not be identified by the SID algorithms. However, the SAM data between the 14259 and 12001, 14260, 15041, 15071 are respectively 0.028, 0.009, 0.0227, 0.0191. These samples can be identified by setting the fine threshold. Therefore, SAM is more effective than SID in that the samples with the same spectral divergence couldn't be identified by SID while can be identified by the SAM method.

5. CONCLUSIONS

To be concluded, SAM, Mahalanobis Distance and Support Vector Machine were recommended for the lunar mineral mapping. At the same time, some particular characteristics

which may be ignored in the earth mineral mapping should be considered in the lunar mineral mapping.

6. ACKNOWLEDGMENT

This research was supported by the National High Technology Research and Development Program of China (Grant No. 2008AA12A212) and the National Natural Science Foundation of China (Grant No. 40571113) .

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