Detection Capability Evaluation of Lunar Mineralogical Spectrometer: Results from Ground Experimental Data postprint

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Abstract

The Chang'E-6 mission will first land on the far side of the moon and bring lunar samples back. As a hyperspectral imager aboard the Chang'E-6 lander, the Lunar Mineralogical Spectrometer (LMS), will achieve the goal of spectral detection and mineral composition analysis in the sampling area, and the data of LMS will also be compared with the results of the returned sample laboratory measurements. Visible and near-infrared hyperspectral remote sensing is an effective tool for lunar minerals identification and quantification. The ground validation experiment can be used to evaluate the detection ability of the LMS. According to the modal abundances of lunar minerals and glasses of APOLLO samples, binary mixed samples, ternary mixed samples, and seven-membered mixed samples were prepared. The samples were ground and stirred homogeneous to about 200 mesh (median particle size about 75 m), to simulate the soil state of the lunar surface. Under the laboratory ambient condition, the 480–3200 nm spectral data of the samples were acquired using the Engineering Qualification Model (EQM) of Chang'E-5 LMS, the performance of which is consistent with the flight model of Chang'E-6 LMS. By fitting the mixed samples' spectral data of the EQM using the Modified Gaussian Methods, the following conclusions can be drawn: The subtle spectral changes of mixed samples can be detected. The modal abundance of low-Ca pyroxene, high-Ca pyroxene, and plagioclase can be derived based on the spectral parameters such as absorption position, depth or width of the mixed samples, and the correlation coefficients R2 are better than 82%, indicating that the LMS has good quantitative detection capability.

Full Text

Preamble

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Detection Capability Evaluation of Lunar Mineralogical Spectrometer: Results from Ground Experimental Data

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Abstract

The Chang'E-6 mission will achieve the first landing on the far side of the Moon and return lunar samples. As a hyperspectral imager aboard the Chang'E-6 lander, the Lunar Mineralogical Spectrometer (LMS) will conduct spectral detection and mineral composition analysis in the sampling area, and its data will be compared with laboratory measurements of the returned samples. Visible and near-infrared hyperspectral remote sensing is an effective tool for lunar mineral identification and quantification. Ground validation experiments can be used to evaluate the detection capability of LMS. Based on the modal abundances of lunar minerals and glasses from Apollo samples, we prepared binary mixed samples, ternary mixed samples, and seven-component mixed samples. The samples were ground and homogenized to approximately 200 mesh (median particle size ~75 m) to simulate the soil state of the lunar surface. Under laboratory ambient conditions, spectral data from 480–3200 nm were acquired using the Engineering Qualification Model (EQM) of Chang'E-5 LMS, whose performance is consistent with the flight model of Chang'E-6 LMS. By fitting the mixed samples' spectral data using the Modified Gaussian Method, we conclude that LMS can detect subtle spectral changes in mixed samples. The modal abundances of low-Ca pyroxene, high-Ca pyroxene, and plagioclase can be derived from spectral parameters such as absorption position, depth, and width, with correlation coefficients R^2 better than 82%, indicating that LMS has good quantitative detection capability.

Key words: methods: data analysis – techniques: spectroscopic – Moon

1. Introduction

With the successful implementation of the Chang'E-5 mission, the Chang'E-6 probe will be launched in 2024. The Chang'E-6 mission will achieve the first landing and sample return from the far side of the Moon. As one of the scientific payloads on the Chang'E-6 probe, the Lunar Mineralogical Spectrometer (LMS) will be responsible for visible and near-infrared spectral detection of the landing area, mineral type identification, and distribution mapping. Additionally, LMS data will be compared with laboratory measurement results from the returned samples.

The composition and distribution of materials on the lunar surface are crucial for studying the origin and evolution of the Moon (Pieters et al. 1993; Williams et al. 1995; Tompkins & Pieters 1999; Jolliff et al. 2000; Elkins Tanton et al. 2002; Cahill et al. 2009; Karthi et al. 2022; Wang et al. 2022). Visible and near-infrared spectroscopy has proven to be a highly effective tool for deriving surface material composition and distribution. It can obtain not only the content and distribution of useful elements such as Fe, Ti, Mg, and Al (Lucey et al. 1998, 2000; Ling et al. 2011a, 2011b; Wu et al. 2012; Yan et al. 2012; Lu et al. 2021), but also the content and distribution of major minerals such as pyroxene, plagioclase, olivine, and ilmenite (Sunshine & Pieters 1993; Pieters 2002; Shkuratov 2003; Shuai et al. 2013). However, significant uncertainties remain in the identification and quantification of lunar surface minerals. For example, the detection and identification of olivine are primarily influenced by the spectral characteristics of pyroxene in lunar soil (Singer 1981; Cloutis et al. 1986; De León et al. 2006). Furthermore, while Mg-olivine (forsterite) and Fe-olivine (fayalite) have quite different spectra with distinct peak positions for their three major bands, allowing clear distinction, high-resolution discrimination of Mg# remains highly uncertain (Clark et al. 2007).

To ensure the payload functions properly and returns high-quality scientific data, LMS requires calibration and ground validation experiments before launch. While the spectral quality of LMS has been evaluated in previous investigations (Cai et al. 2019), this paper prepares binary mixed samples, ternary mixed samples, and seven-component mixed samples based on the distribution characteristics of typical lunar surface minerals. By measuring sample spectra and fitting the data using the Modified Gaussian Model (MGM), we analyze LMS's mineral quantification capabilities.

2. Instrument Overview

LMS consists of a two-dimensional scanning motor and a spectrometer (Liu et al. 2022). The spectrometer includes a Visible and near-infrared imaging detector (VIS, 480–950 nm) and three infrared single-point detectors (NIR, 900–1450 nm; SWIR, 1400–2300 nm; MWIR, 2200–3200 nm). The main characteristics of LMS are listed in Table 1 .

LMS carries a calibration target for in situ radiometric calibration, which is embedded on the inner side of the dust cover. When the lander touches down on the Moon, the dust cover opens and fixes at a 70° angle, exposing the calibration target to sunlight at that angle. LMS detects the landing area by adjusting the observation angle via the two-dimensional pointing mechanism and achieves field-of-view alignment with the calibration target to complete in situ radiometric calibration.

3. Experimental Methods

3.1. Experimental Samples

Based on typical lunar surface minerals and glasses, we prepared six mineral samples and one simulated glass sample. The mineral samples included clinopyroxene (augite), orthopyroxene (hypersthene), olivine, ilmenite, apatite, and plagioclase. All mineral samples (except plagioclase) were ground to 200 mesh (~75 m), similar to the median particle size of lunar soil (40–130 m). Pure plagioclase samples were obtained by crushing and grinding gabbro to 40 mesh (~420 m) first, then removing magnetic minerals with a magnetic separator. The simulated glass samples were prepared by mixing different mineral samples according to the modal abundances in Table 2 , then sintering at high temperature (1150°C for three hours), quenching, and grinding to 200 mesh.

All mineral and glass samples were analyzed for chemical composition using a sequential X-ray fluorescence spectrometer, with results shown in Table 3 and Figures 1 [Figure 1: see original paper] and 2 [Figure 2: see original paper]. To simulate lunar soil mineral composition, we prepared binary mixed samples, ternary mixed samples, and seven-component mixed samples. Sample descriptions and experimental purposes are shown in Tables 4 through 7 . The spectra of all minerals and mixed samples from 480–3200 nm were measured and displayed in our previous paper (Cai et al. 2019).

3.2. Experimental Environment and Process

The experiment was conducted in a dark room, as shown in Figure 3 [Figure 3: see original paper]. Spectral data for seven mineral samples and 18 mixed samples were acquired sequentially using the Engineering Qualification Model (EQM) of LMS and standard spectrometers (ASD and DP102F). Full spectral data of calibration targets (an aluminum panel and a gold panel) were also acquired simultaneously. After reflectance data calculation, spectral parameters for absorption centers, depths, and widths were derived.

4. Detection Capability Evaluation

4.1. Binary Mixed Samples

Binary mixed samples were prepared by mixing augite and hypersthene in different proportions (Table 5). We acquired spectra of these samples, analyzed subtle spectral changes with mineral content, and evaluated LMS's ability to quantify constituent minerals.

As the composition of binary mixed samples changed, the absorption centers and depths varied systematically. Using MGM to fit the spectra, we identified a functional relationship between augite modal abundance and the absorption depth ratio at 2000 nm, defined as the absorption strength of the hypersthene component divided by that of the augite component. The fitting results show that as augite modal abundance increases, the absorption depth ratio at 2000 nm decreases gradually (Figure 4 [Figure 4: see original paper]), with a polynomial fitting coefficient $R^2 = 0.99$. Figure 5 [Figure 5: see original paper] demonstrates the MGM results for binary mixed samples, showing that hydration bands near 3 m are fitted by three Gaussians beyond the data noise level (Hiroi et al. 2021).

4.2. Ternary Mixed Samples

Ternary mixed samples were prepared by mixing hypersthene, olivine, and plagioclase, with a fixed hypersthene-to-olivine ratio but variable plagioclase content. We acquired spectra of these samples, analyzed spectral changes, and evaluated LMS's detection capability for plagioclase quantification.

With increasing plagioclase content, the reflectance amplitudes increase, and the plagioclase absorption peak depth near 700 nm—defined as the strength of the Gaussian around 700 nm fitted by MGM—becomes more pronounced, while pyroxene absorptions near 1000 and 2000 nm gradually weaken. MGM fitting establishes a functional relationship between plagioclase modal abundance and absorption depth at 700 nm. The results show that higher plagioclase content corresponds to deeper absorption at 700 nm (Figure 6 [Figure 6: see original paper]), with a polynomial fitting coefficient $R^2 = 0.82$. Figure 7 [Figure 7: see original paper] shows the MGM results for ternary mixed samples.

4.3. Seven-Component Mixed Samples

Seven-component mixed samples were prepared by mixing augite, hypersthene, olivine, plagioclase, ilmenite, apatite, and simulated glass according to mineral contents in Apollo lunar soil samples. We acquired spectra of these samples and analyzed the relationship between spectral characteristic variations and mineral content to evaluate LMS's ability to identify and quantify various minerals.

As mineral contents changed, both absorption characteristics and reflectance amplitudes of the seven-component mixed samples varied. MGM fitting established functional relationships between hypersthene modal abundance and absorption width at 1000 nm, and between augite modal abundance and absorption position at 1000 nm. The fitting results are shown in Figures 8 [Figure 8: see original paper] and 9 [Figure 9: see original paper], with correlation coefficients $R^2 = 0.91$ and $R^2 = 0.62$, respectively. We attempted to find relationships between other minerals' modal abundances and MGM spectral parameters but obtained no satisfactory fitting results. Figure 10 [Figure 10: see original paper] shows the MGM fitting results for seven-component mixed samples.

5. Conclusions and Discussion

5.1. Conclusion

Ground validation experiments were conducted in the laboratory using the LMS EQM, with spectral data acquisition and MGM modeling performed on binary, ternary, and seven-component mixed samples. The results demonstrate that LMS can effectively detect subtle spectral variations in mixed samples. The quantification model for binary mixed samples correctly reflects the relationship between augite modal abundance and the absorption depth ratio at 2000 nm, with correlation coefficient $R^2 = 0.99$. The ternary mixed samples model properly reflects the relationship between plagioclase modal abundance and absorption band depth at 700 nm, with $R^2 = 0.82$. Additionally, quantification models for augite and hypersthene in seven-component mixed samples were established, with correlation coefficients $R^2 = 0.91$ and $R^2 = 0.62$, respectively. These results demonstrate that LMS has good spectral identification and quantification capabilities.

5.2. Discussion

Quantification models for plagioclase, olivine, ilmenite, simulated glass, and apatite were not established for seven-component mixed samples. Several factors may explain this limitation. First, while MGM allows direct spectral analysis without end-member spectra, it can only quantify minerals with distinct absorption features. Apatite, present at very low concentrations, lacks obvious absorption features except for structural water absorption near 2.7 m, making identification and quantification difficult. Additionally, the low olivine content in seven-component mixed samples prevents its quantification from mixture spectra despite its obvious absorption features near 1 m. The low albedo and low concentration of ilmenite in mixed samples also hinder its identification and quantification. Furthermore, although plagioclase and simulated glass have relatively high modal abundances, their contents vary within a narrow range (e.g., plagioclase only varies from 14.3% to 17.2%), resulting in insufficient spectral variation for reliable modeling.

Previous studies by Pieters et al. (2014) indicate that plagioclase absorption features are suppressed by pyroxene when mixed with it, and plagioclase can only be identified and quantified when its content in the mixture exceeds approximately 80%.

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