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Automated identification of basalt spectra in Clementine lunar data

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ABSTRACT

The identification of fresh basalt spectra plays an important role in lunar stratigraphic studies; however, the process can be time consuming and labor intensive. Thus motivated, we developed an empirically derived algorithm for the automated identification of fresh basalt spectra from Clememtine UVVIS data. This algorithm has the following four parameters and limits: $BC\ Ratio = 3(R950-R900)/(R900-R750) < 1.1$, $CD\ Delta = (R1000-R950)/R750 - 1.09(R950-R900)/R750 > 0.003$ and < 0.06, $B\ Slope = (R900-R750)/(3R750) < -0.012$, and $Band\ Depth = (R750-R950)/(R750-R415) > 0.1$, where $R750$ represents the unnormalized reflectance of the 750 nm Clementine band, and so on. Algorithm results were found to be accurate to within an error of 4.5% with respect to visual classification, though olivine spectra may be under-represented. Overall, fresh basalts identified by the algorithm are consistent with expectations and previous work in the Mare Humorum area, though accuracy in other areas has not yet been tested. Great potential exists in using this algorithm for identifying craters that have excavated basalts, estimating the thickness of mare and cryptomare deposits, and other applications.

1. Introduction

Identifying the presence of basalts, either in surface or subsurface deposits, is a fundamental tool for understanding the two- and three-dimensional distribution of volcanic rocks on the Moon. For example, the delineation and quantification of cryptomare deposits relies on the identification of dark-haloed craters (Schultz and Spudis, 1979; Antonenko et al., 1995), which excavate buried basalts. Similarly, mare thickness studies use basalts in impact craters to determine if the mare basement has been penetrated (e.g., Budney and Lucey, 1998; Thomson et al., 2009).

Fresh basalts, and their constituent minerals, are often identified using spectral methods (e.g., Pieters, 1978; Antonenko, 1999). However, a drawback with this kind of work is the multitude of spectra that must be examined. With multispectral satellite data, spectra are generally extracted from pixels of interest and visually evaluated on an individual basis (e.g., Tompkins and Pieters, 1999), but with literally millions of data pixels in even a modest study area, this can quickly become an extremely time consuming endeavor (at 1 spectra per second, a million spectra would take approximately 278 h to examine). Thus, the user must pick and choose which pixels to inspect for their spectral study. As a result, individual spectra that clearly display mafic absorption features may not even be found. Similarly, entire areas that are spectrally interesting, but otherwise indistinct, may be completely overlooked by this type of study.

Another concern with the inspection of individual spectra is the fact that visual characterization of spectra can be subjective. Firstly, variations in the location and depth of absorption features can be subtle (e.g., Adams, 1974) making it extremely difficult to visually distinguish between different spectra. Secondly, mixing of different materials can produce a range of spectra that grade from one endmember to another (Adams, 1974). Visually identifying a meaningful boundary between these can be difficult and doing so consistently is often not possible.

Many authors, therefore, turn to spectral mixture analysis (SMA), which can be used to detect the presence of basaltic components in a spectral mixture (e.g., Mustard et al., 1998). However, SMA can be very complex and time consuming in itself. Furthermore, SMA excels at identifying percentages of different spectral endmembers. Thus, if the goal is to identify different mineral or chemical compositions of basalts in a mare area, SMA is a very useful tool. However, if the goal is to identify the presence of any and all basalts, regardless of composition, SMA analysis will require extra steps to combine the various compositional results together. Also, because of the complexity involved in defining regional spectral endmembers for SMA, it does not readily lend itself to automation.

Motivated by these issues, we developed an empirical technique for automatically identifying fresh basalt spectra in a Clementine ultraviolet and visible (UVVIS) data scene.

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2. Study area

For our study area, we chose the region west of Mare Humorum (Fig. 1) on the western limb of the Moon. Previous work in this area (e.g., Lucey et al., 1991; Hawke et al., 1993; Antonenko, 1999; Antonenko and Osinski, 2009) provides a good reference for judging the accuracy of our results. The data consists of high resolution (303.23 pixels/deg) Clementine UVVIS multispectral data and color ratio composite images, along with Lunar Orbiter (LO) photographic image data (512 pixels/deg), all downloaded from the UGGS Map-A-Planet PDS Imaging Node website (http://www.mapaplanet.org/explorer/moon.html). Wt% FeO values were calculated from the Clementine UVVIS data using the equations of Lucey et al. (2000a).

3. Training method

In Clementine UVVIS data, fresh basalt reflectance spectra have specific characteristics, most notably an absorption feature in the 1 μm range caused by Fe crystal field transitions (e.g., Adams, 1974). An ideal fresh basalt spectrum is shown in Fig. 2. The first segment (A) has a positive slope, corresponding to the ultraviolet continuum. The second segment (B) has a negative slope, contributing to the obvious band depth, which characterizes 1 μm Fe^{2+} absorptions in pyroxenes and olivines (e.g., Burns, 1993). Finally, the transition from segment B to C to D is a smooth curve that represents the minima of the 1 μm iron absorption feature, with the exact position of the minima depending on variations in mineralogy and chemistry (e.g., Burns, 1993). Spectra which do not exhibit this smooth curve may suffer from calibration artifacts and so are not considered as valid fresh basalt spectra. Automation of fresh basalt spectra identification requires that the relationships between the segments of fresh basalt spectra be numerically understood and modeled using concise parameters.

In order to quantify the significant parameters of fresh basalt spectra, we selected two very different training areas (their locations are shown in Fig. 1), which are known to contain mafic

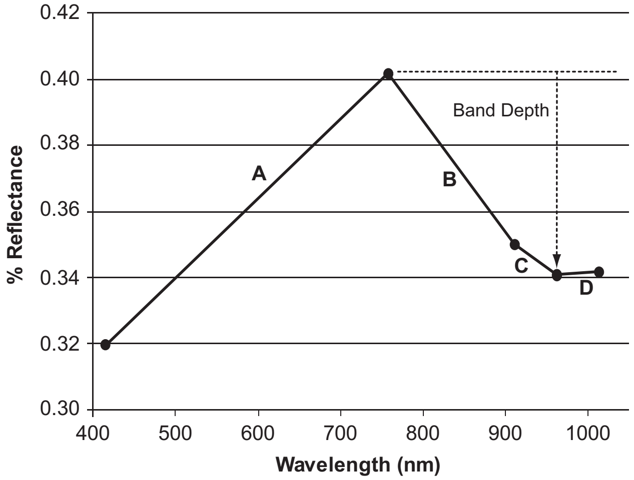

Fig. 2. Ideal fresh basalt spectra from Clementine data showing placement of the four segments, and the model relationship between segments B–D.

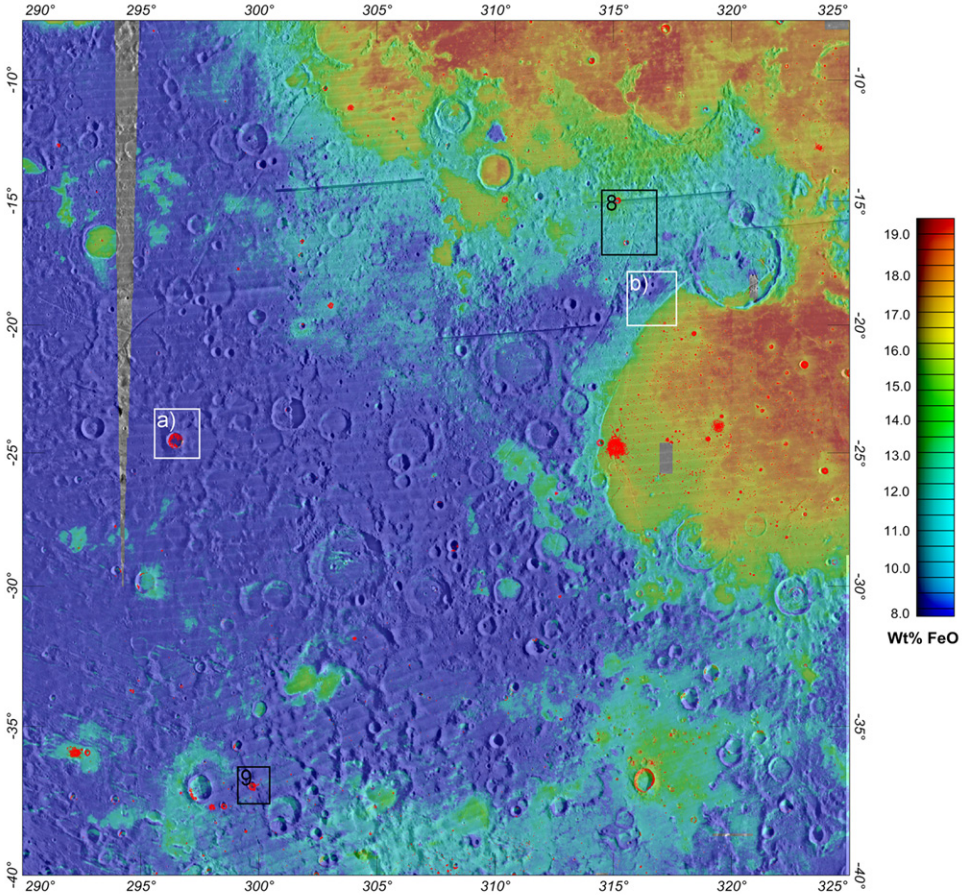

Fig. 1. Lunar Orbiter (LO) image of the Humorum study area, with Lucey et al. (2000a) iron overlay. White boxes show locations of the two training areas (Fig. 3). Locations of fresh basalt spectra identified by the developed algorithm are shown as small red dots. Black boxes show the locations of Figs. 8 and 9. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)