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ABSTRACT

We have developed new methods for enhanced surface material identification and mapping that integrate visible to near infrared (VNIR, \( \sim 0.4 - 1 \mu m \)), short wave infrared (SWIR, \( \sim 1 - 2.5 \mu m \)), and long wave infrared (LWIR, \( \sim 8 - 12 \mu m \)) multispectral and hyperspectral imagery. This approach produces a single map of surface composition derived from the full spectral range. We applied these methods to a spectrally diverse region around Mountain Pass, CA. A comparison of the integrated results with those obtained from analyzing the spectral ranges individually reveals compositional information not exhibited by the VNIR, SWIR or LWIR data alone. We also evaluate the benefit of hyperspectral rather than multispectral LWIR data for this integrated approach.

Keywords: near infrared, short wave infrared, long wave infrared, hyperspectral, classification, fusion, remote sensing, thermal infrared

1. INTRODUCTION

Spectral remote sensing potentially provides a fast, accurate means of characterizing surface composition, leading to improved understanding of the Earth and its complex natural and man-made systems. The majority of research and applications utilizing this tool, however, have been focused on an individual spectral range – most commonly either the visible to near infrared (VNIR, \( \sim 0.4 - 1 \mu m \)), short wave infrared (SWIR, \( \sim 1 - 2.5 \mu m \)), or long wave infrared (LWIR, \( \sim 8 - 12 \mu m \)) regions. This common approach may be particularly limiting where multiple surface materials and complex lithologies cannot be adequately characterized by a single spectral range. Because each wavelength region is sensitive to different properties, materials without distinctive features in one range commonly have a unique character in another. Little attention has been given to exploiting the complementary information provided by the full spectral range. Our goal is to improve the accuracy and effectiveness of the identification and mapping of surface materials by integrating data from the full VNIR-SWIR-LWIR spectral range.

1.1 Site description

We focus the application of this new approach on the region surrounding Mountain Pass, California (Figure 1). This is a rural desert environment with sparse vegetation. The landscape is dominated by several mountain ranges; these exhibit a diverse combination of geologic materials, as shown in Figure 2, including sedimentary (e.g., sandstone, siltstone, shale, limestone, dolomite), igneous (e.g., granite, diorite, andesite, basalt, rhyolite), and metamorphic (e.g., gneiss, amphibolite, migmatisit) rocks\textsuperscript{1,2}. Numerous faults and crosscutting intrusions give further evidence of the area’s complex geologic history. Some intrusions are of unusual composition; in particular, Mountain Pass is known for the occurrence of a unique carbonatite deposit containing rare earth element (REE)-rich minerals\textsuperscript{3}. Multiple mines exist in the area, but of particular note is the active Mountain Pass mine. This mining facility, along with the Ivanpah Solar...
Power Facility, a golf course, the city of Primm, Nevada, and the roads connecting them, introduce man-made materials into the scene.

Figure 1: Study region near Mountain Pass, California. The solid black outline approximates the coverage of the more extensive data set. The dashed and dotted outlines show the footprints of the less extensive data sets.
Figure 2: A simplified surface map indicating general lithology and notable features within the study area. Based upon the surficial and geologic maps of Schmidt and McMackin\textsuperscript{1} and Miller et al.\textsuperscript{2}
1.2 Data description

Spectral data from three instruments are used in this work. The VNIR-SWIR imagery is from the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), a hyperspectral imaging (HSI) sensor that measures radiance in 224 bands between 0.4 and 2.5 \( \mu m \). We employ two different sets of AVIRIS data; one that covers the study region with three overlapping images at 15.5 m/pixel, collected on 5/03/2013 (images f130503t01p00r10, 11, 12), and another that covers a smaller subset of the area with 4 overlapping images at \(-3.4\) m/pixel that is approximately coincident with the more extensive AVIRIS data set and was collected on the same day, 5/03/2013 (image 1394200_06). The hyperspectral LWIR data is from the Mako sensor and was provided by the Aerospace Corporation. Mako measures radiance in 128 spectral bands from 7.6 to 13.15 \( \mu m \). We use data collected on 9/24/2013 in the continuous area scanning mode that is composed of 34 crosstrack scans, or “whisks”, with a pixel size of 1.4 m. The coverage is within the area encompassed by the 2012 AVIRIS data.

These four sets of data were divided into two pairs based on roughly similar spatial resolution and coverage, to provide two examples of VNIR-SWIR-LWIR integration. The first combines hyperspectral VNIR-SWIR data with multispectral LWIR data, pairing the 2013 AVIRIS data with the MASTER LWIR data. The second combines the less extensive 2012 AVIRIS hyperspectral VNIR-SWIR data with the hyperspectral LWIR Mako data, providing an opportunity for insight into the effect of spectral resolution in the LWIR range.

2. METHODOLOGY

Before analysis, the data were pre-processed to convert them from at-sensor radiance to surface reflectance (for VNIR-SWIR) or emissivity (for LWIR). The analysis was conducted in two main stages. An initial spectral analysis was performed independently for each spectral range. Integrated analysis and classification were used in the second stage to produce a final surface map derived from the full spectral range.

2.1 Data preparation

Atmospheric contributions were removed from both VNIR-SWIR data sets with the radiative transfer model-based Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) algorithm. The few areas that returned a water vapor retrieval error (e.g., some locations containing liquid water, clouds, or high mountain peaks) were masked from analysis. Any remaining noise or errors consistent throughout the spectra within an image were reduced with Empirical Flat Field Optimal Reflectance Transformation (EFFORT) polishing. An additional set of corrections was applied to the three 2013 AVIRIS images covering the full study region. First, slight spectral differences between the images were adjusted through an empirical line correction that matched several small homogenous areas in the overlapping portions of the images. Then, field-collected reflectance spectra of a bright and a dark target were linked with the corresponding image pixels, and an empirical line correction was used to modify the image spectra to fit these ground truth data. The smaller spatial extent of the 2012 AVIRIS images did not allow for these two ground targets to be used for additional correction of their spectra, but an empirical line correction was applied that adjusted the 2012 AVIRIS data to match the fully atmospherically corrected 2013 AVIRIS reflectance data in several corresponding regions with satisfactory results. Finally, the multiple images that compose each of these data sets were appended to one another in the ‘y’ (or along-track) direction to allow for simultaneous analysis.

A similar model-based atmospheric compensation approach was used for the hyperspectral LWIR Mako data. Noise affected the first three spectral bands of these data, and they were excluded from processing. The Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes – Infrared (FLAASH-IR) algorithm is designed to address the additional complexities of the LWIR spectral region in order to isolate and remove the atmospheric transmission, upwelling, and downwelling radiance components. Temperature-emissivity separation of the atmospherically corrected radiance was performed with the emissivity normalization method, specifying a maximum emissivity of 1.0. A small number of pixels composed of highly reflective materials could not be processed by this algorithm and were masked from subsequent processing. Excessive noise necessitated the additional masking of a small number of lines in consistent
positions within each whisk of the collection. To include all portions of the data in the spectral analysis procedure, the 34 whisks were appended to one another in the long axis (or across-track) direction.

The multispectral LWIR MASTER data were atmospherically corrected using the In-Scene Atmospheric Compensation (ISAC) approach\textsuperscript{11}. The limited number of spectral bands does not allow for the model-based approach used with the hyperspectral data sets. The same emissivity normalization method, using a maximum emissivity of 1.0, was applied to separate temperature and emissivity. Two spectral bands in the MASTER data exhibited excessive line to line noise related to detector issues that could not be adequately corrected, and therefore bands 41 (7.8 μm) and 45 (9.67 μm) were removed from further analysis.

2.2 Single range spectral analysis

To analyze the spectral regions independently, we separated the AVIRIS spectra into VNIR (≤ 0.995 μm) and SWIR (≥ 1.004 μm) portions. The SWIR portion also excluded the water vapor regions at 1.263 – 1.483 μm and 1.792 – 2.067 μm. The extent of the MASTER and Mako LWIR spectra were as previously described.

Spectral analysis of each range and data set followed a standardized procedure focused on extraction and mapping of the endmember spectra present in an image\textsuperscript{12}. These endmembers, when linearly combined in proportion to their aerial distribution, describe the data’s spectral variability. A Minimum Noise Fraction (MNF) transformation was separately applied to each spectral range. This re-structures the data by separating its signal-dominated components from the progressively more noise-dominated components\textsuperscript{13}. The subsequent steps used only the initial, non-noise MNF bands (the exact number varied with each data set), reducing noise and spectral dimensions. The Pixel Purity Index (PPI), an automated measure of the number of times each image pixel was located at the edge of the data cluster during repeated projection of n-dimensional scatterplots, was used to spatially reduce the number of pixels to be analyzed\textsuperscript{14}. The pixels with the highest PPI values are the most spectrally pure or unique, representing possible image endmembers. These were interactively displayed for further consideration using n-dimensional scatterplotting\textsuperscript{15}. Repeated 2-d projections were used to visualize the structure of the data cluster, and the pixels at the vertices were selected as the endmembers for each data set. Mixture-Tuned Matched Filtering (MTMF), partial unmixing, was used to estimate the apparent abundance of each endmember within each pixel throughout the image\textsuperscript{12}. The MTMF algorithm augments the standard MF measure of difference from the background covariance with an evaluation of the feasibility of that background and target spectrum mixture given physical linear mixing constraints. An increasing infeasibility value indicates a decreasing probability that the given endmember abundance is accurate. For each data set we determined an infeasibility threshold value; an infeasibility value had to be below this threshold for its corresponding apparent abundance value to be considered feasible. Infeasible abundances were set to zero. The end result of this spectral analysis procedure was an image cube for each data set consisting of layers of endmember abundance images in the ‘z’ direction.

All of the analysis results were geometrically corrected after processing using flight ephemeris data. The AVIRIS VNIR and SWIR data sets with three (2013) and four (2012) images were further adjusted by selecting a central image, spatially warping adjacent images to match the base image, and then mosaicking. The 34 Mako whisks were also mosaicked, but fine-tuning of their relative alignment has not yet been accomplished. The single MASTER image was georeferenced using the flight ephemeris data only.

2.3 Integration and classification

The VNIR and SWIR apparent abundance data, both acquired by AVIRIS, were simply stacked in the ‘z’ direction for analysis. Fusions with the LWIR apparent abundance data, however, required matching these data to the VNIR-SWIR data; we co-registered, warped, and resampled the lower-spatial-resolution data set of each pair to match its higher-spatial-resolution partner (i.e., MASTER LWIR to 2013 AVIRIS VNIR-SWIR and 2012 AVIRIS VNIR-SWIR to Mako LWIR), using triangulation and nearest neighbor resampling. Then the LWIR apparent abundance data were stacked with the VNIR-SWIR data, resulting in two joined data sets of 1) VNIR-SWIR-(multispectral)LWIR and 2) VNIR-SWIR-(hyperspectral)LWIR apparent abundance images.

We applied an ISODATA unsupervised classification routine to each of the two joined abundance data sets. This clustering method uses a few simple specified parameters, but no training data or user guidance, to divide the input data
into groupings sharing similar properties. In the specific terms of our application, it separates the input pixels into groups exhibiting similar endmember abundances throughout the full VNIR-SWIR-LWIR spectral range. The constituent pixels in each of the resulting clusters were designated as a class and displayed to produce a final classification map describing the surface composition.

3. RESULTS

3.1 2013 AVIRIS and MASTER integration

The MNF transform of the 2013 AVIRIS VNIR data isolated 14 non-noise bands that were then used to find 33 image endmembers. An infeasibility threshold of 20 was used to separate infeasible MTMF abundances for all of these endmembers. Figure 3 provides a simplified illustration of the endmember distribution, where each pixel was assigned to the endmember with the highest abundance. Pixels with no single endmember at an abundance of >30% were not mapped. The spectra of the predominant endmembers are also shown in Figure 3. The Class 6 and Class 15 endmember spectra exhibit VNIR features related to iron oxide minerals, and are mapped within many different rock types. The Class 32 endmember spectrum displays a decrease in reflectance near 1 µm that is consistent with the 1 µm feature in gypsum, and its distribution matches well with gypsum-bearing playa deposits. Endmembers 12 and 33 have spectra with relatively high reflectance and no distinct features; they are modeled at high abundances in the playa deposits but are also abundant within several carbonate units in the western part of the region. The spectrum of endmember Class 17 is that of vegetation. The Class 19 endmember spectrum contains the unique features of the rare earth element neodymium. Other endmember spectra not shown (and not easily visible in the map), include numerous buildings and other man-made materials.

Analysis of the SWIR portion of the 2013 AVIRIS data used 14 non-noise MNF bands to retrieve 48 spectral endmembers. The feasible MTMF apparent abundance values were limited to an infeasibility threshold of 25 for all endmembers. Several endmember spectra differed only slightly from one another, for example, in overall reflectance, and in these cases the abundance values of those endmembers were combined for each pixel. To assist in visualization of these analysis results, the pixels were mapped according to their dominant endmember group for abundances greater than 30% (Figure 4). This map is dominated by muscovite and/or illite (Classes 3 & 5), dolomite (Class 7), and calcite (Class 8) endmembers. Other SWIR endmembers are observed in more localized areas, such as vegetation (Class 1), gypsum (Class 2), rare earth element-bearing phases (Class 20), and man-made materials (not shown).

The decreased dimensionality of the MASTER LWIR multispectral data was evident in the spectral analysis results, which found four non-noise MNF bands and 28 image endmembers. A single infeasibility threshold to determine feasible MTMF apparent abundance values was not appropriate for all endmembers, so we applied the value determined to be the best for each endmember individually. The small number of bands makes absolute identification of materials using the MASTER spectra alone difficult. A simplified map of the endmember distributions (Figure 5), created by classifying each pixel according to its dominant endmember with an abundance of 30% or greater, provides additional information. In contrast to the limited spatial extent of the areas mapped by the VNIR and SWIR endmembers, the LWIR endmembers describe much of the study area. Several endmembers are strongly associated with a particular surface unit, such as the Class 1 gypsum endmember, the silica-rich Class 3 endmember that matches well to siliciclastic rock locations, endmember Classes 9 and 11 of the playas, and the Class 10 carbonate-bearing endmember, which distinctly models the carbonate units excepting those of the Spring Mountains in the northeast part of the region. Understanding this particular observation requires more investigation. The Class 17 endmember exhibits a slightly different behavior; though its spatial extent appears to conform to unit boundaries, it is mapped with several units, including metamorphic, plutonic, and siliciclastic rock types. Similarly, the Class 25 endmember is found in both siliciclastic rocks and the metamorphic rocks in the northwest part of the region. Endmember Class 28 is associated with different surface types as well as compositions. It is present within siliciclastic rocks and much of their surrounding eroded sediment, and is also widely mapped in the carbonate rocks and sediment of the Spring Mountains in the northeast part of the region. The distribution of the Class 20 endmember matches well with the plutonic rock unit in the Spring Mountains, in addition to much of the alluvium and unconsolidated materials of the study area.
Figure 3: Simplified abundance map and prevalent endmember spectra from 2013 AVIRIS VNIR spectral analysis. Each pixel is classified according to its predominant endmember. Pixels with endmember abundances < 30% are not classified.
Figure 4: Simplified abundance map and prevalent endmember spectra from 2013 AVIRIS SWIR spectral analysis. Each pixel is classified according to its predominant endmember. Pixels with endmember abundances < 30% are not classified.
Figure 5: Simplified abundance map and prevalent endmember spectra from MASTER LWIR spectral analysis. Each pixel is classified according to its predominant endmember. Pixels with endmember abundances < 30% are not classified.
ISODATA cluster analysis of the joined VNIR-SWIR-LWIR endmember abundance data returned 53 classes and produced the classification map shown in Figure 6. The full range-derived results appear generally similar to the LWIR results, particularly in the extent of materials mapped and their agreement with known surface units. Numerous differences are observed, however, corresponding to the influence of the VNIR and SWIR individual analyses. The playa deposits at Mesquite Dry Lake in the northern part of the region are one example (Figure 7). Large areas determined to be spectrally similar in SWIR and LWIR analyses are separated by the integration analysis into two classes. One corresponds to a high abundance in VNIR endmember Class 33 and the other to a low abundance for that endmember. Similarly, a difference in SWIR endmember abundances (e.g., Class 8) distinguishes Class 47 from Class 21 in the integrated classification even though their VNIR and LWIR endmember abundances increase and decrease in parallel. Complete investigation of the complex information revealed by the integrated analysis is ongoing.

3.2 2012 AVIRIS and Mako integration

The spectral analysis procedure isolated 16 non-noise MNF bands in the 2012 AVIRIS VNIR data and found 48 image endmembers. Many of these endmember spectra resemble those extracted from the more extensive 2013 AVIRIS data. Additional endmember spectra were located, probably related to a decrease in sub-pixel mixing at this higher spatial resolution. The materials identified include iron oxides, vegetation, rare earth element-bearing phases, and a variety of man-made objects. Twenty-six non-noise MNF bands were used in the analysis of the 2012 AVIRIS SWIR imagery. We extracted 46 spectral endmembers from this data set, which correspond to muscovite and/or illite, carbonate, rare earth element-bearing phases, kaolinite, vegetation, and numerous buildings and other man-made materials. The Mako hyperspectral LWIR data yielded 22 non-noise MNF bands, a notable increase from the four bands isolated in the multispectral LWIR data. Forty-eight endmember spectra were extracted from the imagery; their identification is ongoing and includes carbonate-bearing materials, quartz-rich lithologies, and reflective roofs and metallic objects. Detailed investigations of the individual spectral analysis results are in progress. Integration of the VNIR, SWIR, and LWIR abundance images through ISODATA cluster analysis returned 45 classes (Figure 8). Examination of this VNIR-SWIR-LWIR classification and comparisons with the single range analyses are underway.

4. SUMMARY AND CONCLUSIONS

We applied a new approach for mapping surface composition utilizing spectral remote sensing data to a diverse region near Mountain Pass, California. This research utilized the capabilities of the full VNIR-SWIR-LWIR spectral range by integrating compositional information generated from independent analyses of each spectral region. The additional detail manifested in the 2013 AVIRIS and MASTER integrated classification, compared to the individual analyses results, successfully illustrates the complementary nature of the VNIR, SWIR, and LWIR spectral range and the potential of this method to enhance current compositional mapping techniques. Ongoing examination of the approach and its results includes consideration of the best tactics to employ for interpreting and applying the added information.

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Figure 6: VNIR-SWIR-LWIR classification map produced from the integration of the 2013 AVIRIS and MASTER data.
Figure 7: Subset of VNIR, SWIR, LWIR, and integrated VNIR-SWIR-LWIR classification images from the 2013 AVIRIS and MASTER analyses illustrating differences in compositions mapped. Plots provide the mean endmember abundance values for selected integration classes.
Figure 8: VNIR-SWIR-LWIR classification map produced from the integration of 2012 AVIRIS and Mako data.
REFERENCES


