MAPPING TARGET SIGNATURES VIA PARTIAL UNMIXING OF AVIRIS DATA

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1. INTRODUCTION AND RATIONALE

A complete spectral unmixing of a complicated AVIRIS scene may not always be possible or even desired. High quality data of spectrally complex areas are very high dimensional and are consequently difficult to fully unravel. Partial unmixing provides a method of solving only that fraction of the data inversion problem that directly relates to the specific goals of the investigation. Many applications of imaging spectrometry can be cast in the form of the following question: "Are my target signatures present in the scene, and if so, how much of each target material is present in each pixel?" This is a partial unmixing problem. The number of unmixing endmembers is one greater than the number of spectrally defined target materials. The one additional endmember can be thought of as the composite of all the other scene materials, or "everything else".

Several workers have proposed partial unmixing schemes for imaging spectrometry data, but each has significant limitations for operational application. The low probability detection methods described by Farrand and Harsanyi (1993) and the foreground-background method of Smith et al. (1994) are both examples of such partial unmixing strategies. The new method presented here builds on these innovative analysis concepts, combining their different positive attributes while attempting to circumvent their limitations. This new method partially unmixes AVIRIS data, mapping apparent target abundances, in the presence of an arbitrary and unknown spectrally mixed background. It permits the target materials to be present in abundances that drive significant portions of the scene covariance. Furthermore it does not require a *priori* knowledge of the background material spectral signatures. Figure 1 illustrates the concept for a scene with five background materials and two targets of interest. The challenge is to find the proper projection of the data that hides the background variance while simultaneously maximizing the variance amongst the targets.

2. METHOD OUTLINE

The data processing can be broken into three steps: reduction to apparent surface reflectance; pixel purity determination; and partial unmixing. The AVIRIS data are first reduced to apparent surface reflectance by a radiative transfer model approach (Gao et al., 1993; Green et al., 1993). This data reduction uses little, or no, ground data and removes the atmospheric, solar and instrument effects.

Next the data are subjected to a dimensionality analysis and noise whitening process, using the Minimum Noise Fraction (MNF) transform process (Green et al., 1988; Lee et al., 1990). Through a series of affine transforms, the data are translated to have zero mean and then rotated and scaled so that the noise in every band is uncorrelated and has unit variance.

Then the data are repeatedly projected onto random unit vectors. The extreme pixels in each projection are noted. A cumulative account records the number of times each pixel is found to be extreme. This extremity-score can be shown to be related to pixel purity, via a convex geometry argument (Boardman, 1993). The purest pixels in the scene arc rapidly identified.

The purest pixels in the scene arc then compared against the target spectra. If any arc close matches for the target materials they are identified and separated from the other purest pixels. This allows the method to work on major scene components. It is not limited to low-probability targets. All high-purity pixels that do not closely match a target spectrum are used to determine a subspace that spans the background. This obviates the need to know the specific background endmember spectra, We only require their spanning subspace, a much less restrictive requirement. Optimal projection vectors arc directly calculated for the target-spanning subspace, perpendicular to the background-spanning subspace.

Automatic unmixing (Boardman, 1993) is applied to the data, after projection onto the optimal target subspace. Here the number of endmembers is one more than the number of targets, irrespective of the complexity of the background. Finally, the target apparent abundances are spatially mapped.

3. AVIRIS EXAMPLES

Wc present three applications of the method: carbonate mapping at the North Grapevine Mountains (NGM), CA / NV; rare-earth mineral mapping at Mountain Pass, CA; and kaolinite mapping near Golden, CO. The carbonate example is shown here for illustration purposes. The NGM scene is fairly complicated and has a variety of surface mineralogies. Figure 2 shows the MNF-eigenvalues, indicating at least six-dimensional data. The targets of interest were calcite and dolomite, two carbonate minerals. The partial unmixing process was applied, and the results are shown in the following figures. Figure 3 shows the optimal projection of the data. The background composite endmember is centered at (0,0). The vertical axis corresponds to the separation between the targets and the background, the horizontal axis maps intertarget separation. The units arc noise standard deviations. Figure 4 shows the MNF model of a target-free scene. The scatter in the null model corresponds to the noise in the data. The agreement between the observed data and the null hypothesis model indicates the successful derivation of the optimal projection. The targets are optimally separated, and the multi-component background is fully compressed.

Figures 5 and 6 show portions of the calcite dolomite abundance maps. For display, the apparent abundances arc scaled from 0.10 to 0.50 and displayed in a gray scale from white to black respectively. The outcrop pattern of the two minerals and surface mixing is clearly defined. Figures 7 and 8 show the mean spectra of the 50 highest abundance pixels for each target. They are good matches to reference spectra of calcite and dolomite.

4. CONCLUSIONS

Wc present a method for mapping target surface materials, based on their spectral signatures, in the presence of complicated and unknown backgrounds. The targets can be major scene components. The spectra of the background materials are not required, The complexity of the unmixing is driven by the number of targets, not by the number of total materials in the scene and background. This uncouples the processing complexity from the scene complexity, The method is rapid, automatic and repeatable.

5. ACKNOWLEDGMENTS

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6. REFERENCES

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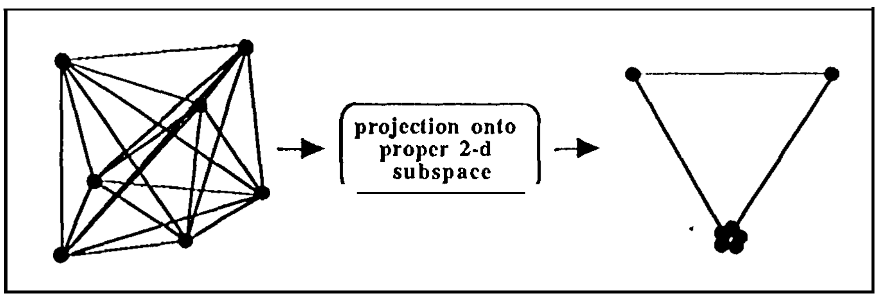


Figure 1. schematic diagram of partial unmixing as a data projection.

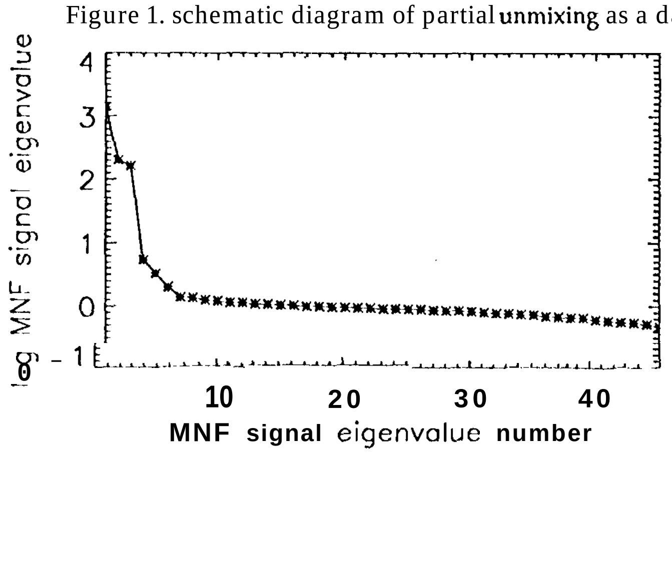
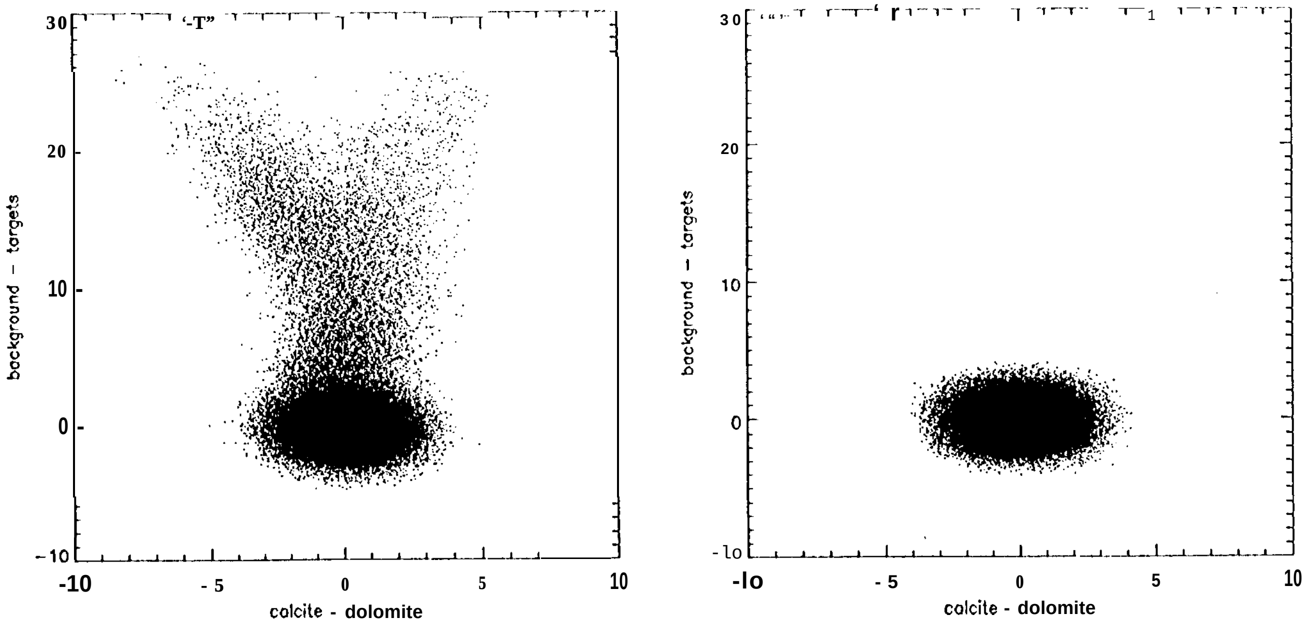
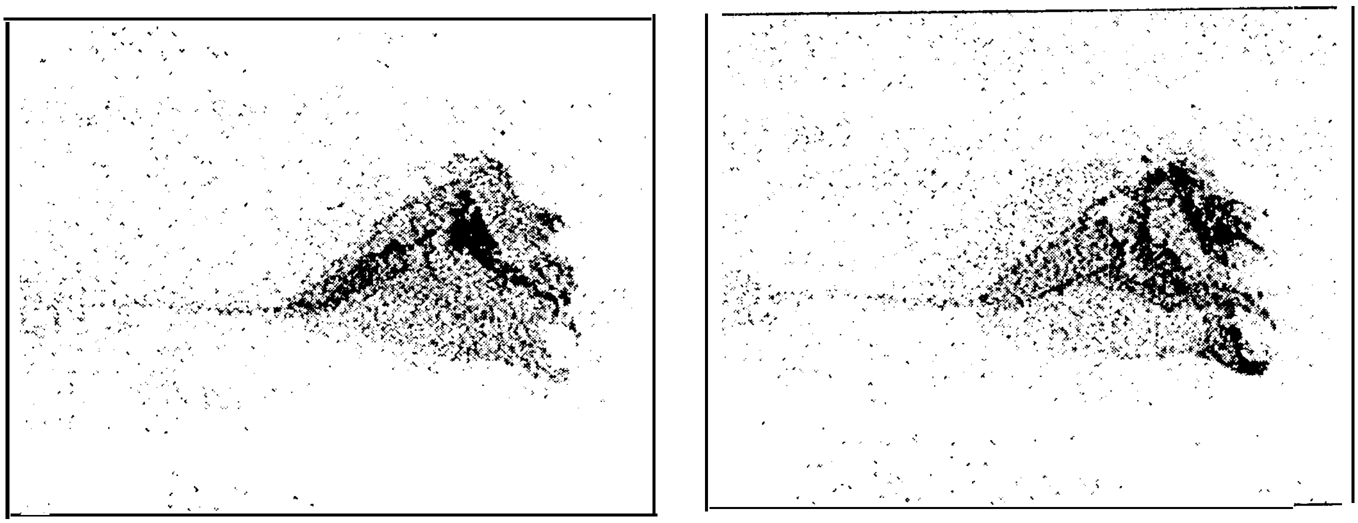


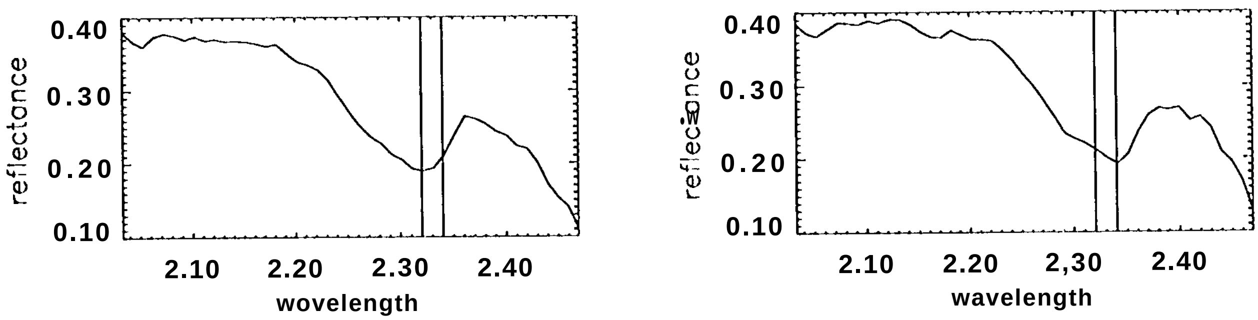
Figure 2, MNF signal eigenvalues of NGM data, showing at least 6 valid dimensions.



Figures 3 and 4. Optimally projected data and MNF-noise-model null hypothesis.



Figures 5 and 6. Apparent abundance of dolomite and calcite target materials.



Figures 7. and 8. Mean spectra of 50 purest dolomite and calcite pixels.