ABUNDANCE ESTIMATION OF SPECTRALLY SIMILAR MINERALS

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1. BACKGROUND AND OBJECTIVE

Spectral unmixing of hyperspectral remote sensing images is proving useful in determining abundances of different minerals. Most spectral unmixing techniques are variants of algorithms involving matrix inversion [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12]. A major problem in spectral unmixing is the non-orthogonality of end-members. Theories behind this are becoming well-established [3, 8].

The ability to estimate abundances in complex mixtures through spectral unmixing techniques is further complicated when considering very similar spectral signatures [13, 14]. It is known that iron-bearing oxide/hydroxide/sulfate minerals have similar spectral signatures. When considering a mixture of the iron-bearing oxide/hydroxide/sulfate minerals, the complexity of estimating these abundances would be related to (a) selection of end-members of iron-bearing oxide/hydroxide/sulfate minerals based on only image data (for a "true" remote sensing case), (b) estimation of partial abundances of end-members and (c) the signal-to-noise ratio (SNR) of the image.

This paper addresses the following three questions, (a) how could estimates of abundances of spectrally similar iron-bearing oxide/hydroxide/sulfate minerals in complex mixtures be obtained using hyperspectral data? (b) what is the effect of the proposed method based on the SNR of the image? and (c) what is the effect of the proposed method when using the most discriminating bands compared to all spectral bands?

2. METHODOLOGY

To address the above three questions, a spectral mixture was generated with varying linear proportions of individual spectra of a set of iron-bearing oxide/hydroxide/sulfate minerals. The set of end-members is commonly associated with sulphide-bearing mine wastes. The first and the second derivatives were then calculated for the different mixed spectrum and the individual spectra of the minerals. It is shown here that most pairs of the derivatives for individual spectra have lower correlation coefficients than the pairs of original individual spectra.

Certain chosen functions, for example the sum and the variance, of the difference between the estimated and actual mixed spectrum is minimized by means of simulated annealing. Prior to unmixing, the mixed spectrum was first subjected to smoothing, using B-Splines, as the derivatives will not necessarily exist in the case of nonsmooth curves. Hyperspectral images, for example DAIS, HyMap and Hyperion each have very different SNR's. In this paper I therefore used SNR of 500:1, 200:1 and 50:1 to see the effect of the proposed method in terms of its accuracy. Furthermore, I selected the most discriminating bands to see if this will have an influence on the results for unmixing as compared to using all the bands.

3. CONCLUSIONS

The variance of the differences between the first derivatives of the observed spectrum and the first derivatives of the end-member spectra give most precise estimates for the partial abundance of each end-member. We conclude that the use of first order derivatives provides a valuable contribution to unmixing procedures provided the SNR is at least 50:1. When the SNR increases, the second derivative of the observed spectrum and the second derivatives of the end-member spectra give most precise estimates for the partial abundance of each end-member. Choosing spectral bands can reduce the correlation between the endmembers and thereby increase the accuracy of the proposed method.

4. REFERENCES

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