TARGET DETECTION IN HYPERSPECTRAL MINERAL DATA USING WAVELET ANALYSIS

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1. INTRODUCTION

Target detection in hyperspectral mineral data is the process of finding the pixels that in some sense match a target spectral signature corresponding to a known mineral. The Hyperspectral Core Imager is a device used to obtain hyperspectral mineral data from mining cores. This presentation discusses the use of wavelet analysis techniques to improve the quality of the hyperspectral data, by mapping the data onto an orthonormal wavelet basis. Additionally, denoising techniques using wavelet thresholding are tested on hyperspectral mineral data.

The high dimensionality inherent in hyperspectral data is reduced using a feature reduction technique known as Sequential Forward Selection (SFS), which uses Receiver Operating Characteristic (ROC) curves as a measure of discriminating capability. Accurate quantitative target detection maps are obtained in a computationally efficient manner for a number of mineral targets, showing the effectiveness of the SFS technique combined with wavelet analysis. These target detection maps are discussed from the viewpoint of mineral identification and unmixing.

2. PROBLEM DEFINITION

The Hyperspectral Core Imager (HCI) is a device owned by AngloGold Ashanti used for obtaining hyperspectral scans of mining cores. Cylindrical mining cores are cut in half, and the flat surface scanned by the HCI to obtain a continuous spectrum ranging from visible light to the shortwave infra-red for each pixel. In the current software implementation, endmember extraction is used to reduce the dimension of the spectral vector associated with each pixel, and the reduced feature set is clustered using self-organising memory [1].

At present, it is not possible to automatically discover the mineral group associated with each cluster, assuming the clusters even correspond to different minerals. It is necessary for a spectral geologist to examine the spectral signatures found in each cluster to identify each mineral. Thus, a problem of target detection can be defined. Given the hyperspectral data of a core scan, and a target mineral to find within the core, is it possible to automatically detect instances of the target in the data in an accurate, quantitative and computationally efficient manner? Furthermore, can we extend this quantitative target detection to spectral unmixing of several targets?

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3. METHODOLOGY

The use of wavelet analysis techniques in hyperspectral data has been shown to provide better results than the traditional analysis techniques of PCA, FFT and DCT [2]. This is due to the non-periodic, non-linear nature of spectral data, where features of interest occur at specific scales and locations. Wavelet techniques are localised to some extent in both time and frequency (or band and scale in the case of spectral data). This allows the decomposition of a spectral signal into localised frequency components. A fast transform is used in this case [3].

This decomposition can be used to denoise signals, since noise resides in high frequencies, and smoother wavelets approximate noise poorly due to vanishing moments. Denoising is necessary for HCI data. A number of denoising techniques [4] [5] were tested to determine if denoising based on wavelet thresholding would improve the quality of the hyperspectral data, and whether this improvement would lead to more accurate target detection.

The high dimensionality of hyperspectral data (and especially the data obtained from the HCI) must be reduced, and so it was necessary to perform feature reduction. This is the process of finding and choosing a subset of features that will lead to the most separability between classes, which in the case of target detection means separating the target from the remaining data.

The feature reduction method used was an extension of the SFS method of [6], which uses ROC curves to measure discriminating capability in a method similar to that of [2]. In this extension, quantitative training data is used, with fuzzy clustering techniques. The reduced features are extracted from the denoised wavelet coefficients and subjected to a simple Euclidean distance classifier. These distances are then used to obtain a quantitative target detection map for each mineral target. Unmixing and mineral identification using these maps is discussed, with respect to sum-to-one and non-negativity constraints. An example of the obtained results is figure 1, showing a quantitative mapping of two different mineral targets in a small section of the core.

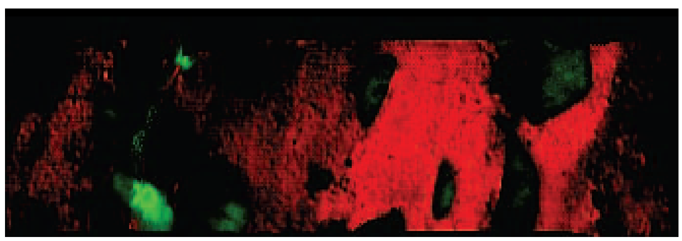

Fig. 1. A quantitative mapping obtained for two mineral targets, showing chlorite-sericite in green and water-phyllosilicate in red.

4. REFERENCES

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