AUTOMATED MINERAL DETECTION IN VISIBLE/NEAR-INFRARED SPECTRA FOR FOCUS-OF-ATTENTION

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Introduction: Hyperspectral systems collect huge volumes of multidimensional data. To identify materials within the spectra, these data must be processed and analyzed. This analysis is time consuming, costly and often requires an expert to robustly identify target compositions by comparison to spectral libraries. On Earth, this may necessitate field checking of targets in a given scene and knowledge of scene-specific parameters e.g. [1, 2 and references therein, 3]. For planetary missions, where global datasets are collected, these data analysis costs restrict rapid classification to only a subset of an entire mission dataset, reducing mission science return.

It is of foremost importance that the amount of science return for a given payload be maximized by suitable information technology. We are developing a series of algorithms to automate the processing and analysis of hyperspectral images to identify constituent spectra. While an ultimate goal would be to accurately classify the composition of every pixel on a planet's surface, this is made difficult by the fact that most pixels are complex mixtures of n materials, which may or may not be represented in library (training) data. We instead focus on the identification of specific important mineral compositions within pixels in the data. Specific targeting is a frequent application of hyperspectral imaging, *e.g.*, minerals associated with acid mine drainage, hydrocarbons, or mineral exploration. For Mars, high priority targets include minerals associated with the presence of water (*e.g.*, carbonates, sulfates, evaporates).

Data downlink restrictions from planetary missions also highlight the need for robust mineral detection algorithms. For example, both OMEGA and CRISM will map only ~5% of the Mars surface at full spatial and spectral resolution. While some targets are preselected for full resolution study (*e.g.*, landing sites), other high priority targets on Mars will be selected in response to observations made by the instruments in a multispectral survey mode. The challenge is to create mineral detection algorithms that can be utilized to analyze any and *all* image cubes (x, y, λ) for a selected instrument. Such algorithms can help ensure that priority targets are not overlooked in these datasets.

We are developing automated supervised algorithms that will rapidly classify hyperspectral data and identify geologically important minerals. These detectors will be tunable to a range of hyperspectral systems, providing a mechanism to search all data for targets of interest. We have focused on the specific application of building detectors to identify minerals in VIS/NIR hyperspectral data collected at Mars. Initially, as an analog to OMEGA and CRISM, we have analyzed data from JPL's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS; 17 m/pixel, 224 bands over 400-2500 nm [4]) instrument.

Methods: A carbonate detector has been created based on a Support Vector Machine (SVM), a classifier that separates data (spectra) into classes based on training on representative samples of both classes. A drawback of SVM algorithms is that large numbers of training data are often required for the algorithm to converge (learn). This makes the cost of collecting a sufficient number of field or laboratory spectra for training prohibitive. We addressed this problem in our previous work by developing a *generative model* for spectra that allows us to obtain spectral data with many of the characteristics of field data at almost no cost. The model mixes spectra drawn from both JPL ASTER [5] and USGS [6] spectral libraries based on mineral compositions (rocks) we specify. Compositions consist of one or more minerals where each mineral has a percent present range (to model modal mineralogy) and is identified to be *essential*, *non-essential*, or *accidental* (rare) to the composition based on terrestrial and martian petrology. This detector has been applied to the analysis of an atmospherically corrected AVIRIS scene of Cuprite, Nevada (Figure 1) to demonstrate the applicability of these detectors to analyze hyperspectral data. The detector was trained and tested on continuum-removed spectra resampled to match the wavelengths in the AVIRIS scene.

Results and Discussion: The detector successfully identified the majority of calcite occurrences in the scene (green areas in Figure1a). **Something about how quickly the classification took place.** Since each mineral detector is focused on only a single mineral (e.g. calcite) or mineral subclass (e.g. carbonate), entire hyperspectral data cubes can be rapidly analyzed. This makes our detectors ideal for use in exploratory data analysis, where rapid feedback enhances discovery potential.

Application to Mars. The algorithm describe here performed well on atmospherically-corrected data, at Mars, we predict that atmospheric correction will be a necessary pre-processing step for analysis. Current classification protocols for OMEGA data have had success applying a generalized atmospheric removal method to all scenes based on the difference in observations collected at the summit and base of Olympus Mons [7,8]. Atmospherically-corrected spectra at Mars still have the issue of ubiquitous dust which serves to greatly reduce the contrast of spectra making them appear very unlike the training data collected from spectral libraries. One solution to this problem involves dividing all spectra in a scene by the spectrum of the dustiest pixel in that scene. However, this requires expert identification of dusty pixels in a given scene. A second solution is to train the classifiers to recognize pixels that contain both a mineral of interest and dust. This can be accomplished by training on areas where minerals have been identified on the Mars surface by experts [9-12].

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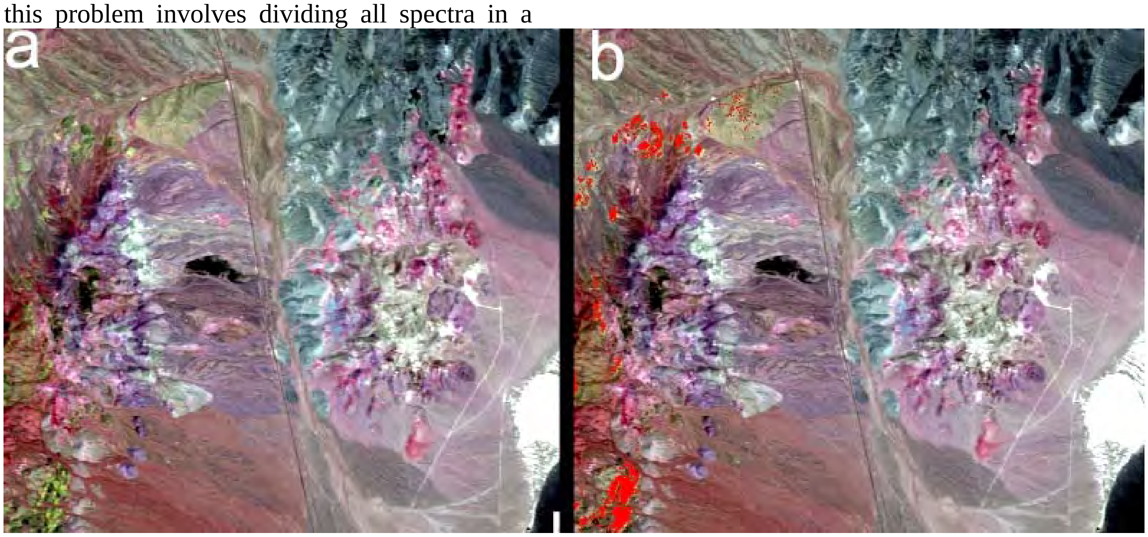

Figure 1. a) Portion of 1995 AVIRIS scene for Cuprite, Nevada. Bands 183 (2101 nm), 193 (2201 nm), 207 (2340 nm) as RGB. A highway runs north-south (north is towards the top) through the center of the image for scale. In this rendition, calcite appears as green hues. b) Same as in (a). Area re identified as calcite by our SVM detector.