

# **Spectral Identification of Minerals using Imaging Spectrometry Data: Evaluating the Effects of Signal to Noise and Spectral Resolution using the Tricorder Algorithm**

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## **INTRODUCTION**

The rapid development of sophisticated imaging spectrometers and resulting flood of imaging spectrometry data has prompted a rapid parallel development of spectral-information extraction technology. Even though these extraction techniques have evolved along different lines (band-shape fitting, endmember unmixing, near-infrared analysis, neural-network fitting, and expert systems to name a few), all are limited by the spectrometer's signal to noise (S/N) and spectral resolution in producing useful information. This study grew from a need to quantitatively determine what effects these parameters have on our ability to differentiate between mineral absorption features using a band-shape fitting algorithm. We chose to evaluate the AVIRIS, HYDICE, MIVIS, GERIS, VIMS, NIMS, and ASTER instruments because they collect data over wide S/N and spectral-resolution ranges. The study evaluates the performance of the Tricorder algorithm (Clark and Swayze, this volume) in differentiating between mineral spectra in the 0.4-2.5  $\mu\text{m}$  spectral region. The strength of the Tricorder algorithm is in its ability to produce an easily understood comparison of band shape that can concentrate on small relevant portions of the spectra, giving it an advantage over most unmixing schemes, and in that it need not spend large amounts of time reoptimizing each time a new mineral component is added to its reference library, as is the case with neural-network schemes. We believe the flexibility of the Tricorder algorithm is unparalleled among spectral-extraction techniques and that the results from this study, although dealing with minerals, will have direct applications to spectral identification in other disciplines.

## **METHOD**

We decided to model only single-component mineral spectra because they allow us to establish the absolute minimum S/N and spectral resolution necessary to distinguish between mineral species. This type of simplified model was adopted with the understanding that multicomponent spectra will require even higher S/N and resolution because of overlapping absorptions and weaker band strengths due to dilution by the other mixture components. Minerals from seven mineral groups (alunite, calcite, chlorite, hematite, kaolinite, montmorillonite, and muscovite) were chosen for evaluation based on the presence of easily detected spectral features and common occurrence at the ground surface. All of these minerals have either Fe charge-transfer and crystal field bands in the VIS/NIR region or  $\text{OH}^-$ , Metal-OH,  $\text{H}_2\text{O}$ ,  $\text{CO}_3^{2-}$ , and  $\text{SO}_4^{2-}$  vibrational features in the NIR region. Some of the minerals have features in both regions.

A bidirectional-reflectance spectrum of each mineral was first deconvolved to the spectral resolution of each imaging instrument, and then scaled random noise was added. Signal to noise is defined here as 50 percent reflectance divided by the standard deviation of the gaussian-noise spectrum, with standard deviation uniform at all wavelengths. To make our determinations statistically accurate, we generated over 20,000 noisy spectra for each convolved mineral spectrum. The S/N levels varied from 1 to 500 as did the number of noisy spectra at each level: 400 for the high S/N levels and up to two thousand at the low S/N levels. These spectra were then analyzed by the Tricorder algorithm and the best matching library mineral spectra chosen for each noisy-spectrum. Tricorder fits the noisy spectra to over 120 library mineral spectra (convolved to the noisy spectrum resolution) by first removing the continuum from diagnostic spectral regions of both the noisy spectrum and library spectra, and then least-squares scaling each library spectral absorption to the corresponding continuum-removed region in the noisy spectrum. During the process of scaling, a linear correlation coefficient, which we

call the "fit," is generated for each library mineral comparison. The mineral with the highest fit is chosen as the best spectral match. Tricorder determines the fit of each library mineral spectrum by individually fitting all the diagnostic absorptions in the library spectrum to the noisy spectrum and then calculating an overall fit by weighting each individual fit by its absorption-feature's area.

Because random noise can make a mineral's spectral features resemble those of other minerals and because this effect is magnified as S/N decreases, we expected Tricorder to choose several different mineral matches, especially at the low S/N levels. We also expected Tricorder to make correct identifications at high S/N levels. Tricorder gave the results that we expected at these S/N extremes. Of particular interest is the S/N region where Tricorder first starts to make incorrect identifications. By plotting the percentage of correct identifications versus S/N level, we can determine precise S/N levels at which the algorithm has a given percent accuracy in identifying this mineral at a given spectral resolution. By plotting the individual incorrect mineral identifications versus S/N we can determine which minerals are most likely to start spectrally resembling the noisy spectrum as S/N decreases. For example, calcite is misidentified 1 out of 9 times at a S/N of 13 at AVIRIS resolution. Stated another way, with Tricorder, we are able to spectrally recognize calcite 90 percent of the time at a S/N of 13 at AVIRIS resolution. The other 10 percent of the time we would either identify calcite as epidote, nontronite, hectorite, dolomite (each of which have strong 2.3- $\mu$ m absorptions) or classify the noisy spectrum as having NO MATCH in the spectral library. As spectral resolution decreases this 90 percent identification level occurs at progressively higher S/N levels.

By compiling the S/N levels for each imaging spectrometer at which 90 percent of the identifications of a mineral are correct, we can quantitatively assess the effects of S/N and spectral resolution for each imaging spectrometer. Preliminary work shows that Tricorder's ability to correctly identify a mineral increases with increasing S/N and spectral resolution.

# PRELIMINARY STUDY OF KELSO DUNES USING AVIRIS, TM, AND AIRSAR

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## 1. INTRODUCTION

Remote sensing of sand dunes helps in the understanding of aeolian process and provides important information about the regional geologic history, environmental change, and desertification. Remotely sensed data combined with field studies are valuable in studying dune morphology (Breed et al., 1979), regional aeolian dynamics (Mainguet, 1984), and aeolian depositional history (Blount and Lancaster, 1990). In particular, active and inactive sands of the Kelso Dunes have been studied using Landsat TM (Paisley et al., 1991) and AIRSAR (Lancaster et al., 1992). In this report, we describe the use of AVIRIS data to study the Kelso Dunes and to compare the AVIRIS information with that from TM and AIRSAR.

## 2. STUDY SITE AND DATA

The Kelso Dunes, Mojave Desert, California, cover about 100 km<sup>2</sup> and range in elevation between 500 m to 900 m. The area of active dunes includes three large linear ridges (up to 170 m high) superimposed by 5-10 m high crescentic and reversing dunes and surrounded by 3-15 m high stabilized transverse and linear dunes (Paisley et al., 1991; Lancaster et al., 1992). Under present conditions, the prevailing westerly winds are counter-balanced by strong orographically controlled winds from the north, east, and south (Smith, 1984). This wind pattern accounts for the position of the dunes and the observation that there is little net change in dune location, even though there is active sand movement (Sharp, 1966). Smith (1967) suggested that the dunes formed under more arid conditions with stronger winds, and have since been modified due to climatic changes. The vegetation cover is less than 5% on the active dunes and 10-15% on the stabilized dunes (Lancaster et al., 1992).

## 3. METHODS

AVIRIS data (PG02031) used in this study were flown on May 21, 1994. The AVIRIS image data were radiometrically calibrated and were reduced to "scaled surface reflectances" using an atmospheric and solar model, ATREM (Gao and Goetz, 1993). The AVIRIS data were then compared with a Landsat composite image (Paisley et al., 1991) and AIRSAR data collected during the Mojave Field Experiment campaign (Arvidson et al., 1991).

A color composite AVIRIS image is used in this preliminary study. The bands were selected using a laboratory spectra plot of major minerals from the dune area so that the spectra are most separated at these bands (Figure. 1). Point counting of field samples show that most of the Kelso sands are composed of 29-49% quartz, 22-39% plagioclase, 18-29% K-feldspar, 5-15% other minerals including dark minerals. Some sites have highly concentrated magnetite (28%; Paisley et al., 1991). Finally, band #10, #89, and #184, centered at 0.46029  $\mu\text{m}$ , 1.2028  $\mu\text{m}$ , and 2.1073  $\mu\text{m}$  respectively, were assigned red, green, and blue in the image analyzed.