Characterizing Image Errors Using the Spectral Mixture Framework

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Summary

Spectral mixture analysis (SMA) has been used to analyze multispectral images from a variety of instruments such as the Phobos 2 Infrared Spectrometer (ISM), Galileo Solid State Imager (SSI), and Landsat Thematic Mapper. We report here on a new approach within the SMA framework for estimating the residual errors in an image's encoded radiance (DN values) and then computing the errors in the estimated fractions of reference endmembers. Error analysis is an essential step for quantifying thresholds of detectability of scene components and for determining the reliability of classifications based on fractions of endmembers.

Introduction

SMA has been applied to images of Mars, the Moon, many environments on Earth, and even galaxies. (A few selections from the SMA literature are given in [1–5].) The SMA approach deals with the problems of sub-pixel spectral mixing, terrain illumination, and calibration by linearly transforming DN values from each pixel into fractions of reference endmembers. The reference endmembers correspond to materials important to an observer in the field, e.g. minerals, rocks, soils, vegetation, etc., each of which has a characteristic reflectance spectrum.

The SMA framework assumes that each pixel in the scene comprises mixtures of endmembers, and that in each spectral band the radiances from these endmembers add linearly. If we know the spectrum of each likely endmember, then by inversion we can find the fractions of each endmember in each pixel. The method requires the analyst to have a good knowledge of the likely scene characteristics, so that reasonable endmembers are selected. From the mixtures of reference endmembers yielded by SMA, an analyst can make classifications that correspond to useful geological or ecological field units.

Error Analysis Framework

Before being analyzed by SMA or any other method, a raw image should be corrected to the fullest extent possible to remove geometric distortion, to co-register all band images to each other, to linearize detector response, and to remove other unwanted instrumental effects. Some residual errors will remain in the DN values even after such correction.

It is particularly important to quantify fraction errors when we are trying to extract information at the edges of the reliability of the data. This is especially true in threshold detection, where insufficient signal to noise may render a particular endmember statistically undetectable [6]. Moreover, relatively small errors in some bands' DN values can create relatively large errors in fractions of some endmembers.

Residual errors can have serious effects on the reliability of the classifications. The classification method in SMA relies upon dividing up endmember space into domains that represent classes of interest. For example, if a pixel has less than X% of endmember A and more than Y% of endmember B, it may be assigned to a certain class. However, if there are significant residual errors in the estimated endmember fractions, then pixels with fractions near the boundaries of X% and Y%, respectively, may be assigned to the wrong class. Conversely, the reliability of our classifications could be characterized if we knew the likely errors in endmember fractions.

In SMA the endmember fractions are derived as linear functions of the DNs. The errors in endmember fractions are therefore also linear functions of the errors in the DNs. Namely, for each pixel, the covariance matrices are related as

$$(\mathrm{cov}_{\text{endmember fraction}}) = P(\mathrm{cov}_{\text{DN values}})P^T$$

P is the matrix that yields the vector of endmember fractions when multiplied by the DN vector.

Thus if we can estimate the covariance matrix of the DNs for each pixel, then the problem can be solved. The approach we have developed is to estimate the DN errors due to every possible source in an instrument, sum them statistically, and then apply the above equation. Important error

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sources in most instruments are misregistration between different band images, optical aberrations and imperfections, electronic and quantization noise, and detector nonlinearities and biases.

Principal Error Sources

In every imaging system each pixel in the detector is "contaminated" to some degree by radiation from nearby pixels. The extent of the contamination can be estimated if we know the instrument's modulation transfer function (MTF) [7] and the underlying spatial frequency properties of the scene down to scales of multiple cycles per pixel. As an example, in the Galileo SSI instrument [8] an average of 43% of the signal from each pixel is contributed by portions of the scene outside that pixel. While this effect will average out across an image, it reduces our certainty in classifying any particular pixel.

Any residual misregistration that remains after applying standard registration algorithms will limit the accuracy of endmember fractions and classification. For example, a Galileo SSI pixel misregistered by 20% of a pixel width in one band with respect to the other bands will have roughly 5% more contamination than if all bands were perfectly registered. Each band has its own MTF, so the error contribution of misregistration will differ accordingly in different bands. Because the MTF will be lower at longer wavelengths (the point spread function is broader), there will be larger errors in estimated fractions of endmembers that are highly reflective at long wavelengths.

Fourier image analysis can be used to assess the errors arising from both the MTF and misregistration. The following is done in each band. First a Fourier transform is developed that represents the underlying sub-pixel spatial frequency properties of the scene, based upon any available or hypothetical knowledge of the properties of the scene. Add to this the Fourier transform of the DN image, divided by the MTF (including corrections for optical distortion). Take the inverse transform of this sum, and resample the new image according to how the bands are misregistered, if this is known. This new image should be an approximation of the original, perfectly registered scene, at least in terms of its spatial frequency components and registration. Compare it to the original DN image to generate a DN covariance matrix that represents the DN errors for an average pixel.

Other possibly important error sources are quantization of the DN values, data roundoff errors, and biases and non-linearities that remain after standard corrections to the raw image. Smearing due to movement of the target during the exposure or between exposures with sequential filters will add further errors to the DNs. The Fourier domain may be the best way to handle this problem much as is done for misregistration. When each likely significant error source has been characterized by a DN covariance matrix, the covariances can be statistically added and the covariance matrix for the endmember fractions computed.

Conclusions

The SMA method provides a useful framework to quantify errors in spectral image analysis. By characterizing these errors, it is possible to determine whether detection requirements can be met. It also becomes possible to evaluate classifications, and to make them more robust to the effects of errors. It may ultimately be possible to improve registration between band images by iterating on different fits between band images until the residual errors are minimized. This work also illustrates that, if the most effective use is to be made of future multispectral imaging instruments, then before flight the MTFs should be measured in all bands to spatial frequencies into the range of multiple cyles per pixel.

References

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