SPARSE CODING FOR SPECTRAL SIGNATURES IN HYPERSPECTRAL IMAGES

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Abstract

The growing use of hyperspectral imagery leads us to seek automated algorithms for extracting useful information about the scene. Recent work in sparse approximation has shown that unsupervised learning techniques can use example data to determine an efficient dictionary with few a priori assumptions. We apply this model to sample hyperspectral data and show that these techniques learn a dictionary that: (1) contains a meaningful spectral decomposition for hyperspectral imagery; (2) admit representations that are useful in determining properties and classifying materials in the scene, and (3) forms local approximations to the nonlinear manifold structure present in the actual data.

Hyperspectral Imagery

Pixels in hyperspectral imagery (HSI) are summations of ground reflectance off of present materials. Portion of the Smith Island HSI Image

Sparsity in HSI

HSI typically employs a linear mixing model, with each pixel represented as a linear sum of component spectra from a dictionary (called endmembers).

Manifold Approximation

HSI data manifolds are typically highly structured in a nonlinear fashion [1]. Structure within a class can be informative, i.e. water depth. The manifold structure for water is linearly approximated by the learned dictionary.

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Dictionary Learning Algorithm

The dictionary learning algorithm from Olshausen and Field [2] is modified for HSI data.

Conclusions

Spectral recovery from MSI measurements taken on a different day from the training set

Spectral recovery from coarse HSI measurements taken on a different day from the training set

Classification Results

The decomposition of spectra into the learned dictionaries retain information vital to material classification applications. Vector Quantization (VQ) show that the coefficient space is informative of material decompositions

Spectral Super-resolution

HSI sensors are relatively rare, expensive to build and require long scan times relative to multispectral imagery (MSI). Sparsity models allow for high resolution spectra to be recovered from coarse measurements, meaning MSI or HSI with faster scan times can be used instead.

References

