SPARSE CODING FOR SPECTRAL SIGNATURES IN HYPERSPECTRAL IMAGES

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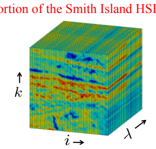
Abstract

The growing use of hyperspectral imagery lead 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.

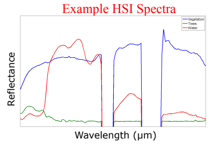
Hyperspectral Imagery

Pixels in hyperspectral imagery (HSI) are summations of ground reflectance off of present materials.

Portion of the Smith Island HSI Image



Example HSI Spectra

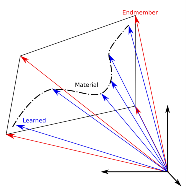


Sparsity in HSI

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

$$\underbrace{x_{i,k}(\lambda)}_{\text{Spectrum at }(i,k)} = \sum_{l=1}^{M} \underbrace{\phi_l(\lambda)\overbrace{a_{i,k,l}}^{l^{\text{th}}\text{ coefficient}}}_{\text{Contribution of }l^{\text{th}}\text{ Dictionary Element}}$$

Sparsity models that find similar linear decompositions with few non-zero coefficients give good results in many problems [3], and algorithms exist to learn optimal sparsity dictionaries from example data [2]. Sparsity models may be particularly effective for HSI, and we expect the learned dictionaries to approximate the non-linear variations in the material spectra.



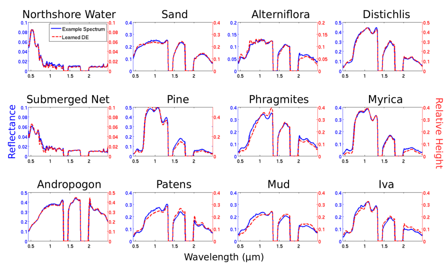
Dictionary Learning Algorithm

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

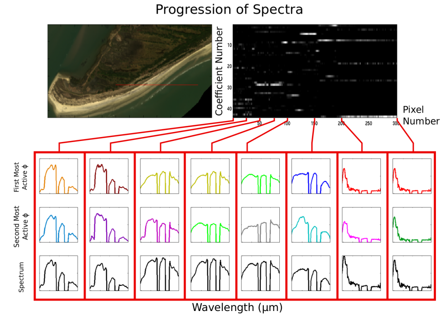
Set $\gamma = 0.01$
Set $\mu = 10$
Initialize each ϕ_l to random positive values
repeat
  for $i = 1$ to 200 **do**
    Choose HSI pixel $x_{i,k}$ uniformly at random
    $\{a_l\} = \arg\min \|x_{i,j}(\lambda) - \sum_{l=1}^{M}\phi_l(\lambda)a_{i,k,l}\|_2^2 + \gamma\sum_{l=1}^{M}|a_{i,k,l}|$ s.t. $a_{i,k,l} \geq 0$
    $\Delta\phi_l(\lambda, i) = a_l\left(x_{i,k}(\lambda) - \sum_{j=1}^{M}\phi_j(\lambda)a_{i,k,j}\right)$
  end for
  $\phi_l(\lambda) \leftarrow \left[\phi_l(\lambda) + \frac{\mu}{200}\sum_i \Delta\phi_l(\lambda, i)\right]_+$
  $\mu \leftarrow 0.995\mu$
until $\{\phi_l\}$ converges

Learned Dictionaries

Learned dictionary elements resemble known material spectra



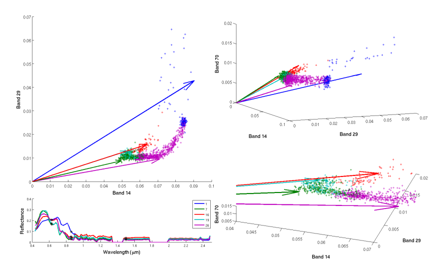
Consistent decompositions are observed in the spatial dimension



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.

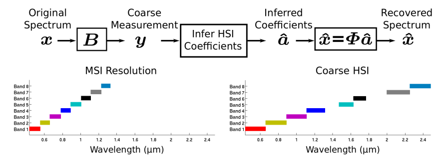
The manifold structure for water is linearly approximated by the learned dictionary



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 coarser measurements, meaning MSI or HSI with faster scan times can be used instead.

Resolution recovery using sparsity models



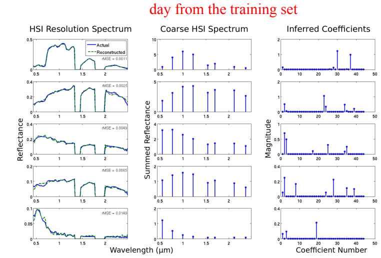
Learned dictionaries recover spectra better than exemplar or random dictionaries for coarse HSI measurements taken on either the same day (SD) or on a different day (DD) than the training data.

	Mean Error (SD)	Median Error (SD)	Mean Error (DD)	Median Error (DD)
44 Learned DE	8.249×10^{-4}	4.911×10^{-4}	7.054×10^{-3}	6.005×10^{-3}
44 Exemplar DE	6.280×10^{-3}	2.709×10^{-3}	1.493×10^{-2}	1.105×10^{-2}
44 Random DE	4.143×10^{-1}	4.524×10^{-1}	3.965×10^{-1}	4.165×10^{-1}

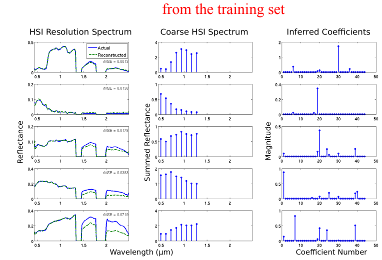
Learned dictionaries also recover spectra more accurately for MSI-level measurements

	Mean Error	Median Error	Mean Error	Median Error
44 Learned DE	1.271×10^{-2}	1.791×10^{-3}	2.456×10^{-2}	1.219×10^{-2}
44 Exemplar DE	1.132×10^{-2}	5.552×10^{-3}	2.225×10^{-2}	2.135×10^{-2}
44 Random DE	7.845×10^{-1}	8.974×10^{-1}	7.775×10^{-1}	9.946×10^{-1}

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



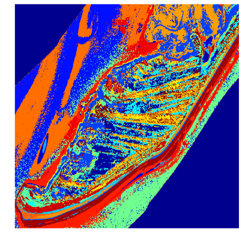
Spectral recovery from MSI measurements taken on a different day from the training set



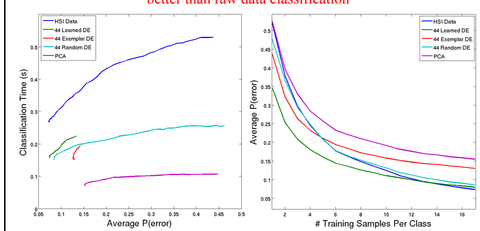
Classification Results

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



Sparse codes retain information vital to classification and generalize better than raw data classification



Conclusions

Sparsity models and dictionary learning algorithms are valuable for HSI analysis. In particular we find that:

1) The learned dictionaries closely resemble true material spectra;

2) These dictionaries capture subtleties within classes, locally approximating the underlying data manifold;

3) Learned dictionaries can be used in a linear inverse setting to super-resolve HSI data from lower resolution measurements with high accuracy; and

4) Learned dictionaries also provide a powerful representation for classification, producing less complex classifiers and better generalization.

Acknowledgments

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References

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