Learning Sparse Codes for Hyperspectral Images

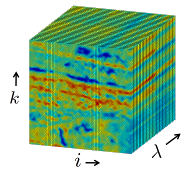
Adam Charles[1], Bruno Olshausen[2], Christopher J. Rozell[1]

[1]*Georgia Institute of Technology*, [2]*University of California, Berkeley*

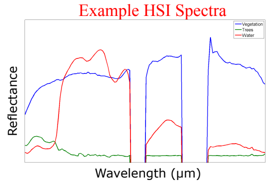
Hyperspectral Images and Sparsity

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

Portion of the Smith Island HSI Image



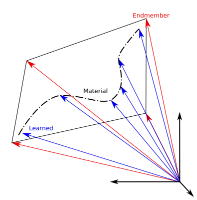
Example HSI Spectra



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

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

Sparsity models may be particularly effective for HSI, and we expect the learned dictionaries to approximate the non-linear variations in the material spectra.

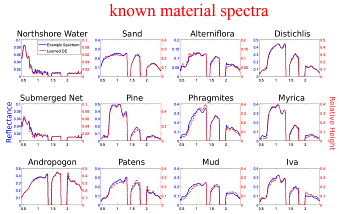


Learned Dictionaries

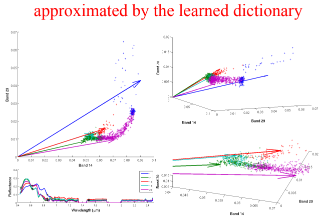
The dictionary learning algorithm from Olshausen and Field (1996) is modified for HSI data.

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

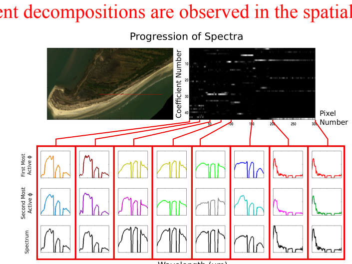
Learned dictionary elements resemble known material spectra



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



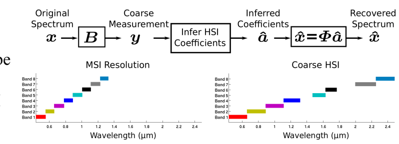
Consistent decompositions are observed in the spatial dimension



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



Good High-resolution recovery from both coarse HSI and MSI-level measurements taken on either the same day (SD) or on a different day (DD) than the training data.

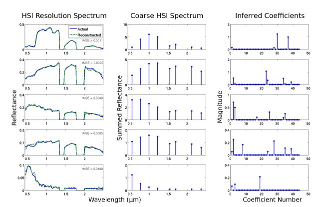
Coarse HSI Measurement Recovery

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

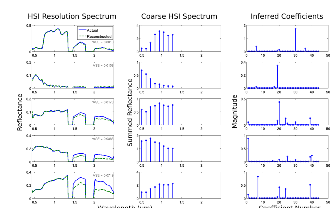
MSI Measurement Recovery

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

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

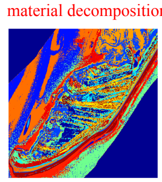


Spectral recovery from MSI measurements taken on a different day from the training set

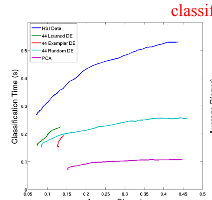


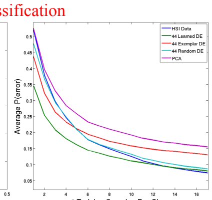
Classification Results

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 HIS 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.

Publications:

[1] A. S. Charles, B. A. Olshausen and C. J. Rozell. ``Learning sparse codes for hyperspectral images", To appear in the IEEE Journal of Selected Topics in Signal Processing, September, 2011

[2] A. S. Charles, B. A. Olshausen and C. J. Rozell. ``Sparse coding for spectral signatures in hyperspectral images", In Proceedings of the Asilomar Conference on Signals, Systems and Computers, Pacific Grove, CA, November 2010

Acknowledgements:

The authors are grateful to Charles Bachmann at the Naval Research Laboratory for generously providing he Smith Island HSI data set and the associated ground truth labels.

Contact Information: acharles6@gatech.edu, crozell@gatech.edu, baolshausen@berkeley.edu