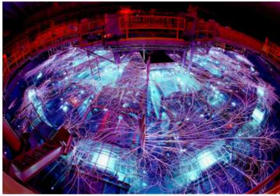
Exceptional service in the national interest

Sandia National Laboratories

SAND2020-2035PE



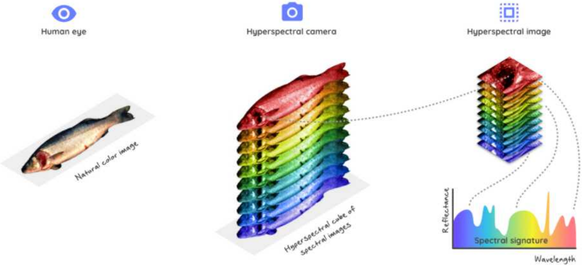
Compressive sensing for hyperspectral imaging

Dennis Lee

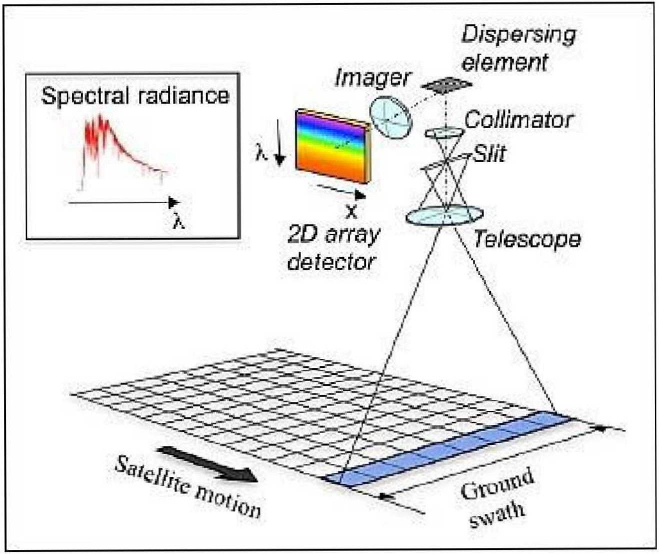
February 19, 2020

oratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia,
neywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract

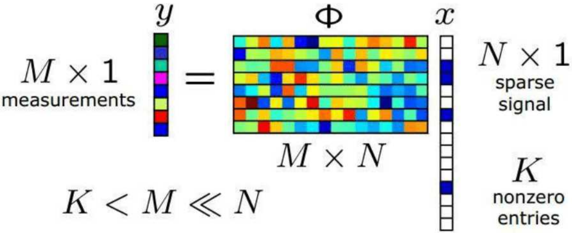
Hyperspectral imaging



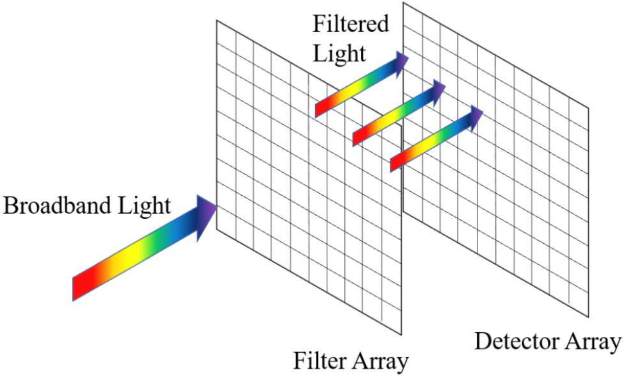
Traditional sensors for HSI



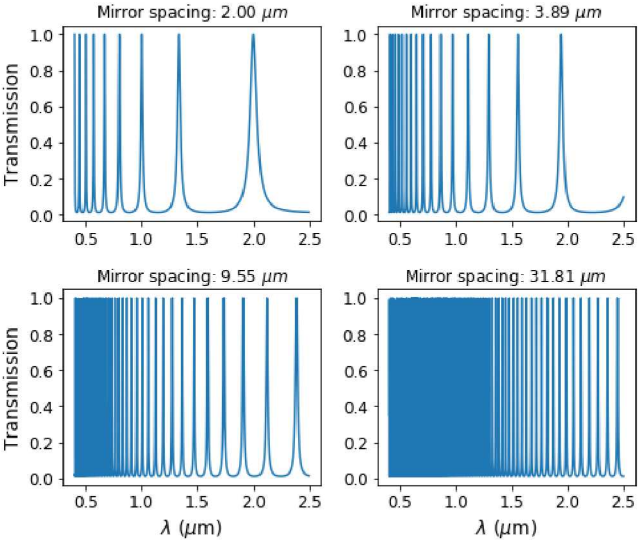
Compressive sensing recovers sparse signals



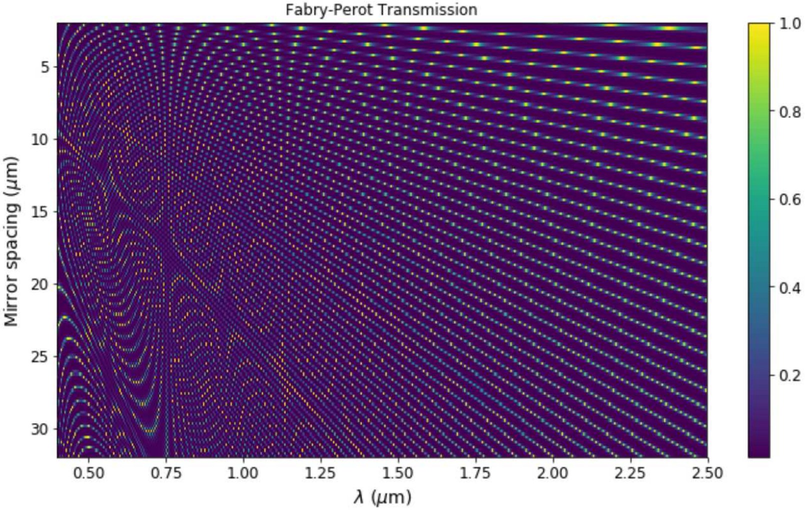
Snapshot hyperspectral imager



Fabry-Perot resonators

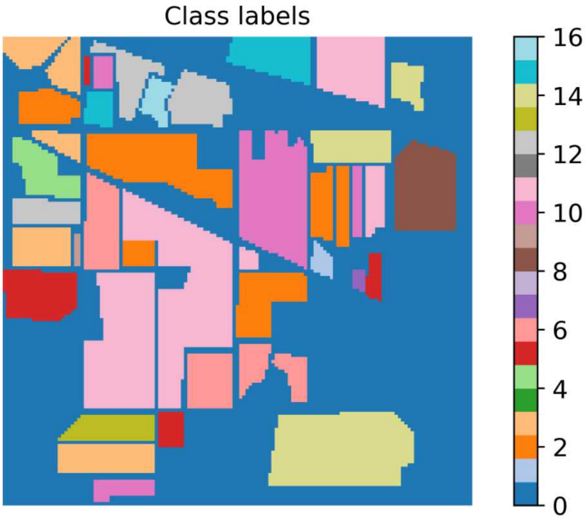


Mirror spacing vs. wavelength



Hyperspectral dataset

- The data cube has size $145 \times 145 \times 220$.
- The measured data cube has size $145 \times 145 \times 160$ with noise added.



Hyperspectral image reconstruction

- $\boldsymbol{A}$ is the transmission matrix.
- For each pixel, solve a penalized likelood problem:

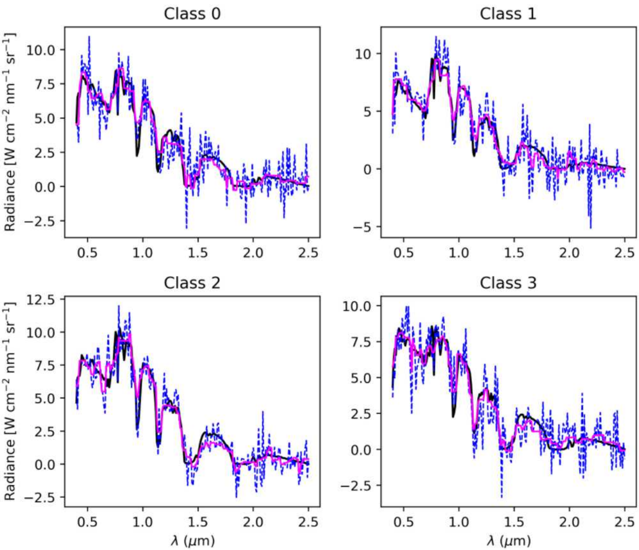
$$\begin{aligned} \underset{\hat{\boldsymbol{x}},\boldsymbol{x}}{\text{minimize}} \quad & \frac{1}{2}\sum_{i=1}^{X}\sum_{i=1}^{Y} ||\boldsymbol{A}\hat{\mathbf{x}}_{i,j} - \boldsymbol{y}_{i,j}||_2^2 + \beta||\hat{\mathbf{x}}_{i,j}||_1 + \mathrm{TV}(\boldsymbol{x}, \boldsymbol{\alpha}) \\ \text{subject to} \quad & \mathbf{x}_{i,j} = \boldsymbol{W}\hat{\mathbf{x}}_{i,j}, \quad 1 \leq i \leq X, \quad 1 \leq j \leq Y \end{aligned}$$

Optimization procedure

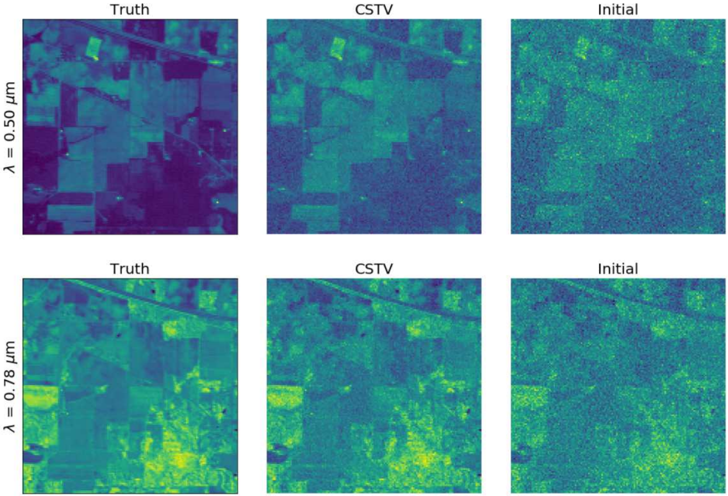
- Update $\hat{\boldsymbol{x}}$, $\boldsymbol{x}$, and $\boldsymbol{p}$ sequentially:

$$
\begin{aligned}
L_\eta(\{\hat{\boldsymbol{x}}_{i,j}\}, \{\boldsymbol{x}_{i,j}\}, \{\boldsymbol{p}_{i,j}\}) = \frac{1}{2} \sum_{i=1}^{X} \sum_{i=1}^{Y} ||\boldsymbol{A}\hat{\boldsymbol{x}}_{i,j} - \boldsymbol{y}_{i,j}||^2 + \beta||\hat{\boldsymbol{x}}_{i,j}||_1 \\
+ \langle \boldsymbol{p}_{i,j}, \boldsymbol{x}_{i,j} - \boldsymbol{W}\hat{\boldsymbol{x}}_{i,j} \rangle + \frac{\eta}{2}||\boldsymbol{x}_{i,j} - \boldsymbol{W}\hat{\boldsymbol{x}}_{i,j}||^2 \\
+ \mathrm{TV}(\boldsymbol{x}, \boldsymbol{\alpha})
\end{aligned}
$$

Example reconstructions

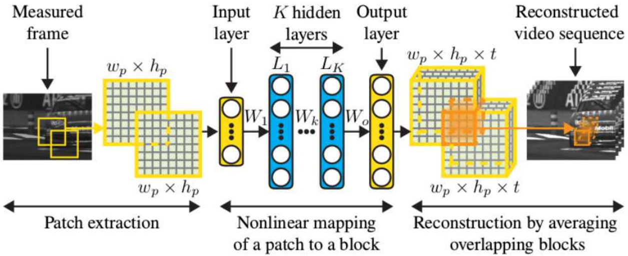


Example images



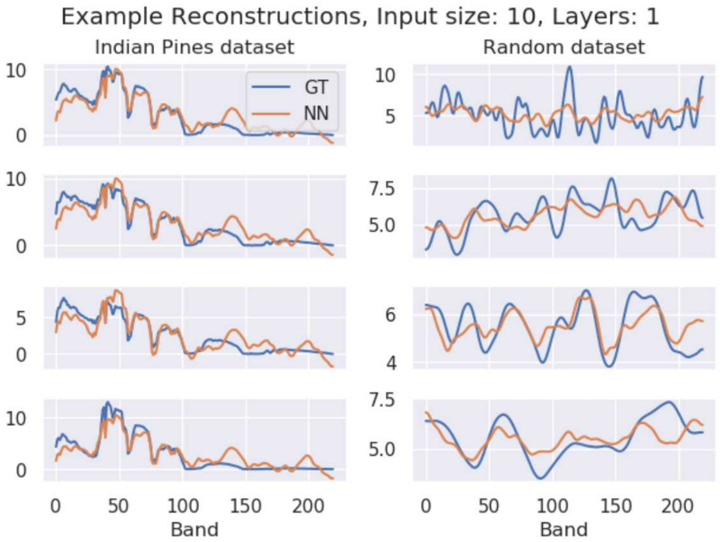
Multi-layer perceptrons for reconstruction

- The dataset contains 21025 spectra (145 x 145). We reserve 60% for training, 20% for validation, and 20% for testing.
- The number of layers varies as K = 1, 2, 4, 7, 14.

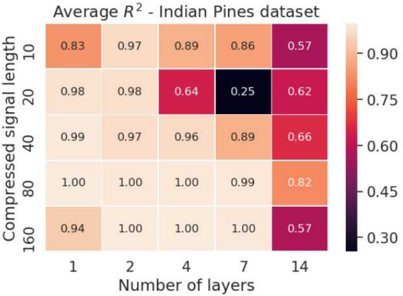


M. Iliadis, et. al., "Deep fully-connected networks for video compressive sensing" arxiv:1603.04930v2 (2017).

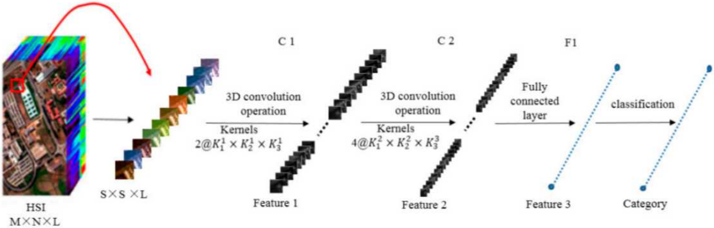
Results from multi-layer perception



Performance with varying layers

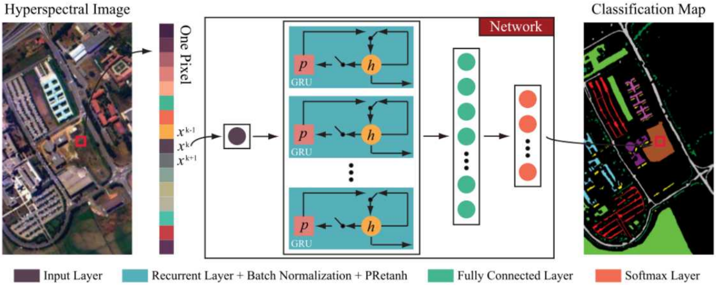


3D convolutions extract spatial and spectral features



Y. Li, et. al., "Spectral-spatial classification of hyperspectral imagery with 3D convolutional neural network" Remote Sens. (2017).

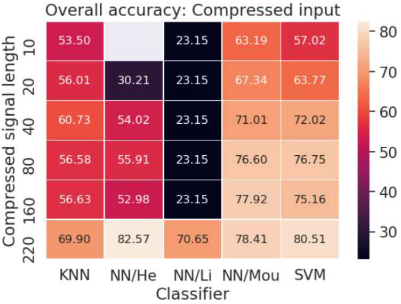
Recurrent networks characterize spectral correlation

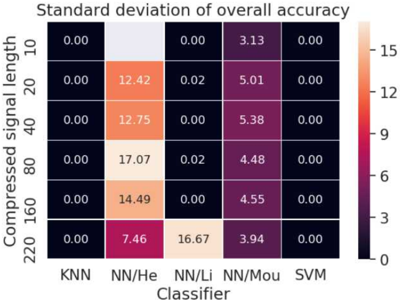


L. Mou, et. al., "Deep recurrent neural networks for hyperspectral image classification" IEEE Trans. Geoscience and Remote Sens. (2017).

Performance as input size varies

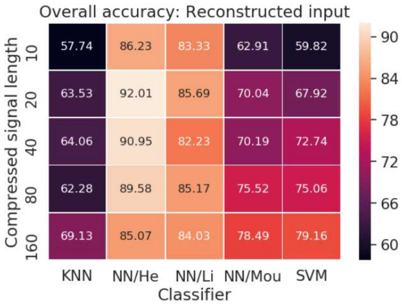
- RNNs (NN/Mou) perform best as input size varies.

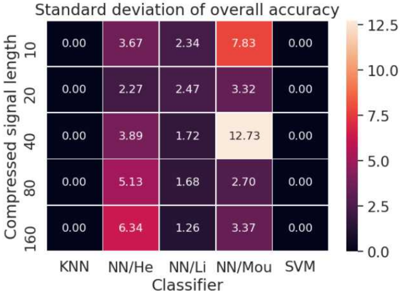




Performance on reconstructed inputs

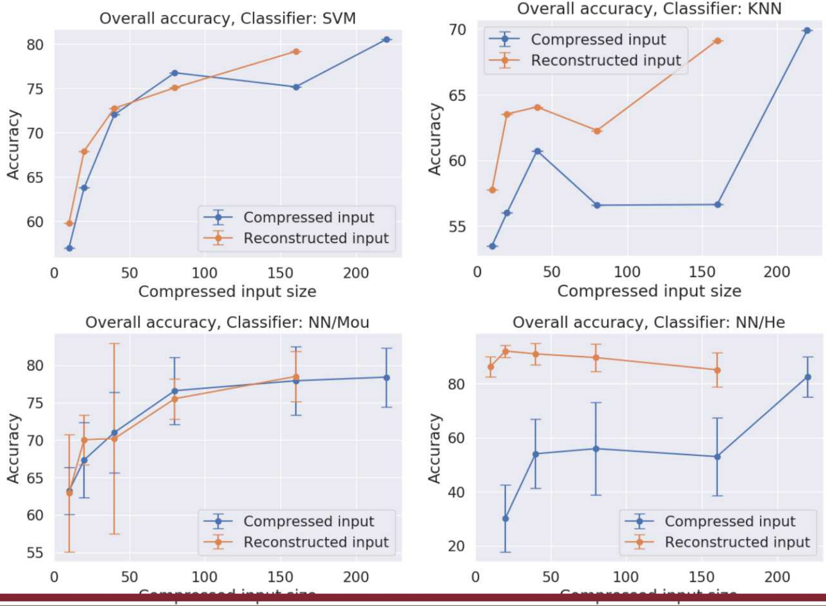
- 3D CNNs (NN/He) perform best as input size varies.





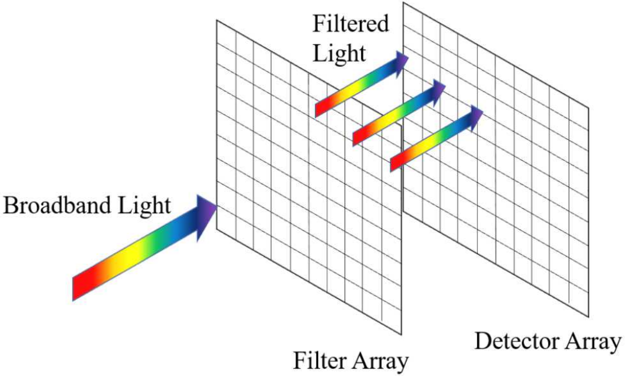
Sandia National Laboratories

Accuracy improves on reconstructed inputs



Summary

- A novel hyperspectral imager has been proposed based on the theory of compressive sensing.
- Reconstruction algorithms and machine learning approaches have been developed to process the hyperspectral data.



References

- D. J. Lee and E. A. Shields, "Compressive hyperspectral imaging using total variation minimization," Proc. SPIE 10768, 1076804 (2018).
- D. J. Lee, "Deep neural networks for compressive hyperspectral imaging," Proc. SPIE 11130, 1113006 (2019).