SAND2019-9014C

Performance Analysis of a Tiled Array Compressive Sensing Snapshot Imaging Spectrometer

Presented by:

Eric A. Shields

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Outline

- Motivation
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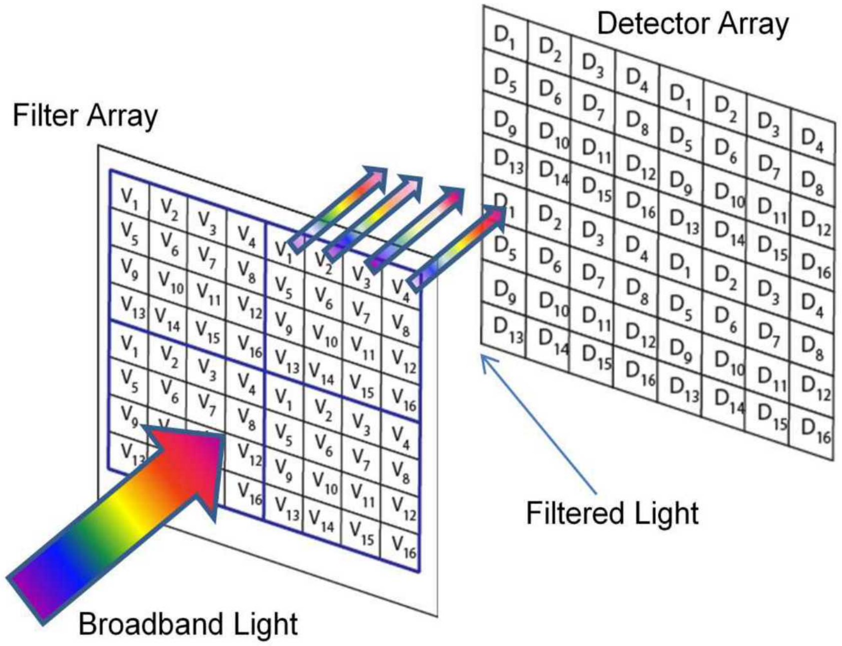
- Spectral Super-Resolution
- Classification of Indian Pines Spectra
- Summary

Motivation

- Compressive sensing (CS) techniques show promise for sensors that collect information with fewer samples than traditional systems.
- CS systems require a computationally-intensive optimization routine to reconstruct the signal into its traditional form – something a human can understand.
- Machine learning algorithms are increasingly being used to perform tasks.
- If a machine is going to perform the task, why bother putting the data into a form a human can understand?
- If the machine learning task can be performed on the CS data in its raw form, then the reconstruction is unnecessary. Benefits of this paradigm include:
  - Reduced computational requirements
  - Faster decision time
  - Simpler machine learning algorithm
- Results for a compressive sensing snapshot imaging spectrometer (CSSIS) are presented.

CSSIS Geometry



- Spatially-tiled filters are placed in front of each pixel of an array detector.
- The filters can be Fabry-Perot etalons, liquid crystal devices, dielectric stacks, nano-antenna arrays, or any other technology that allows the spectral transmittance to be varied from one element to another.

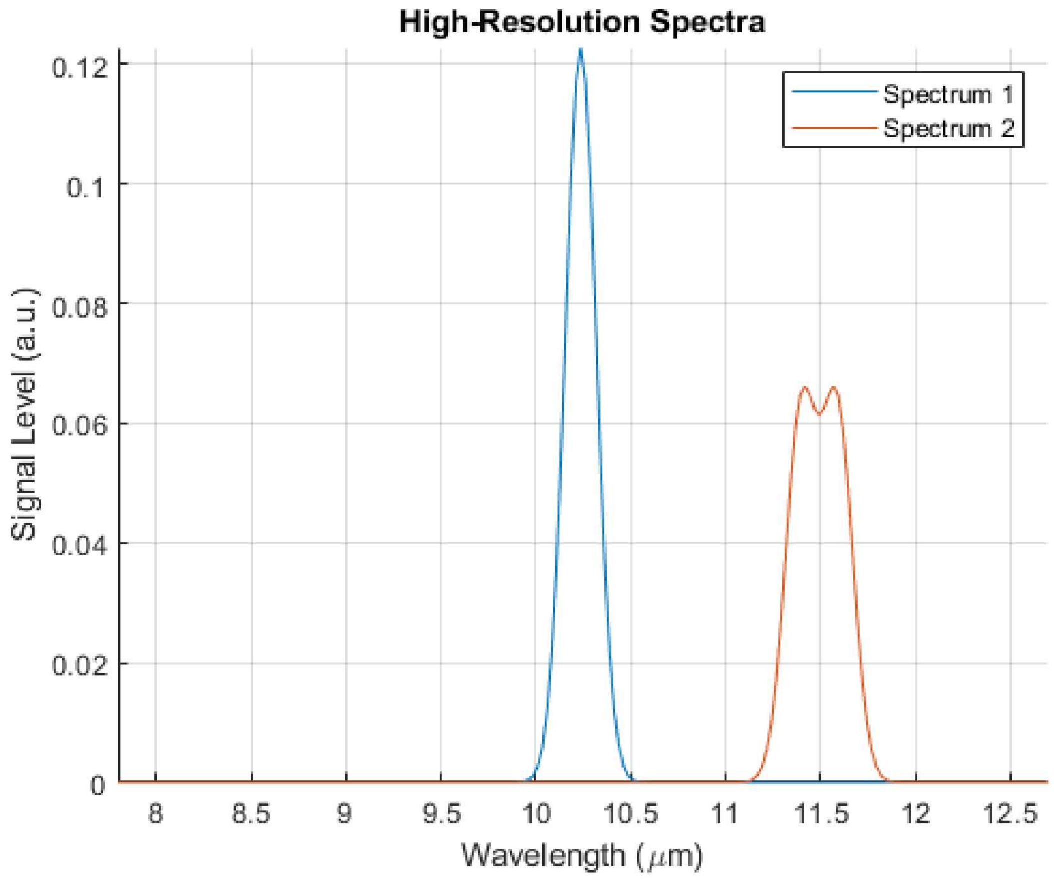
CSSIS Benefits

- The CSSIS potentially has increased spectral resolution.
  - Traditional digital cameras use a 2x2 array to make measurements in 3 spectral bins (red, green, blue).
  - Traditional tiled array spectrometers use an NxN array to make N^2 measurements.
  - By appropriately designing the filters, compressive sensing techniques can allow more spectral bins than measurements.
- The CSSIS potentially has increased optical throughput.
  - Traditional tiled array spectrometers use a set of narrowband spectral filters. Most of the light hitting an individual filter is lost.
  - The CSSIS can use filters with high average transmittance across the system passband.
- The CSSIS filters are potentially easier to fabricate.
  - Traditional tiled array spectrometers often use spectral filters with sharp edges, which are hard to fabricate.
  - The CSSIS filters do not need sharp edges.
- By using CS techniques, the trade-space between spectral resolution, spatial resolution, and area coverage is positively impacted.

Spectral Super-Resolution

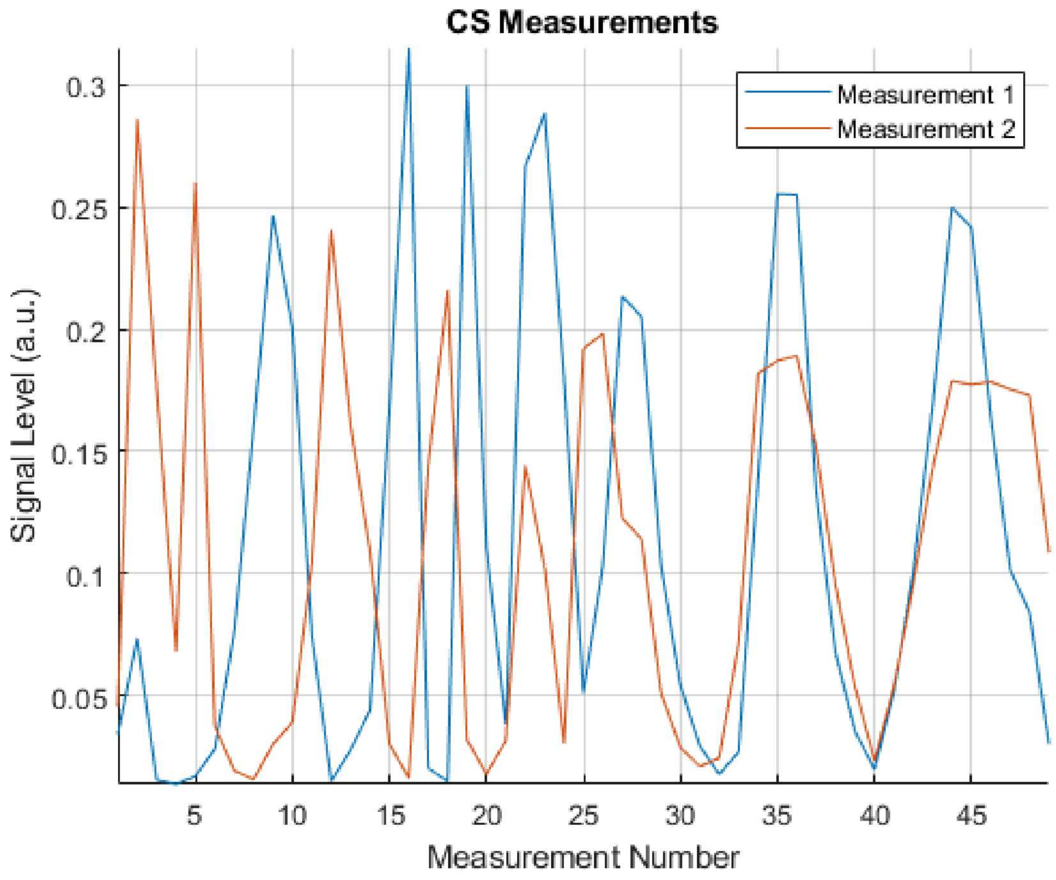
- Question: Can the CSSIS outperform a traditional tiled spectrometer in terms of spectral resolution?
- A 7x7 array CSSIS with Fabry-Perot etalons was simulated for the wavelength regime of 7.8 to 12.7 μm.
  - Mirror reflectances were all 80%.
  - Mirror thicknesses ranged from 47.33 to 99.24 μm.
  - A compression factor of 4X is used.
- A 7x7 array traditional tiled array spectrometer was simulated for comparison.
  - Ideal, non-overlapping filters with unity transmittance and a spectral width of $1/49^{th}$ of the spectral regime were simulated.
- Two spectra were simulated.
- No spatial variation in spectral content was assumed.

Spectral Super-Resolution: Input Spectra



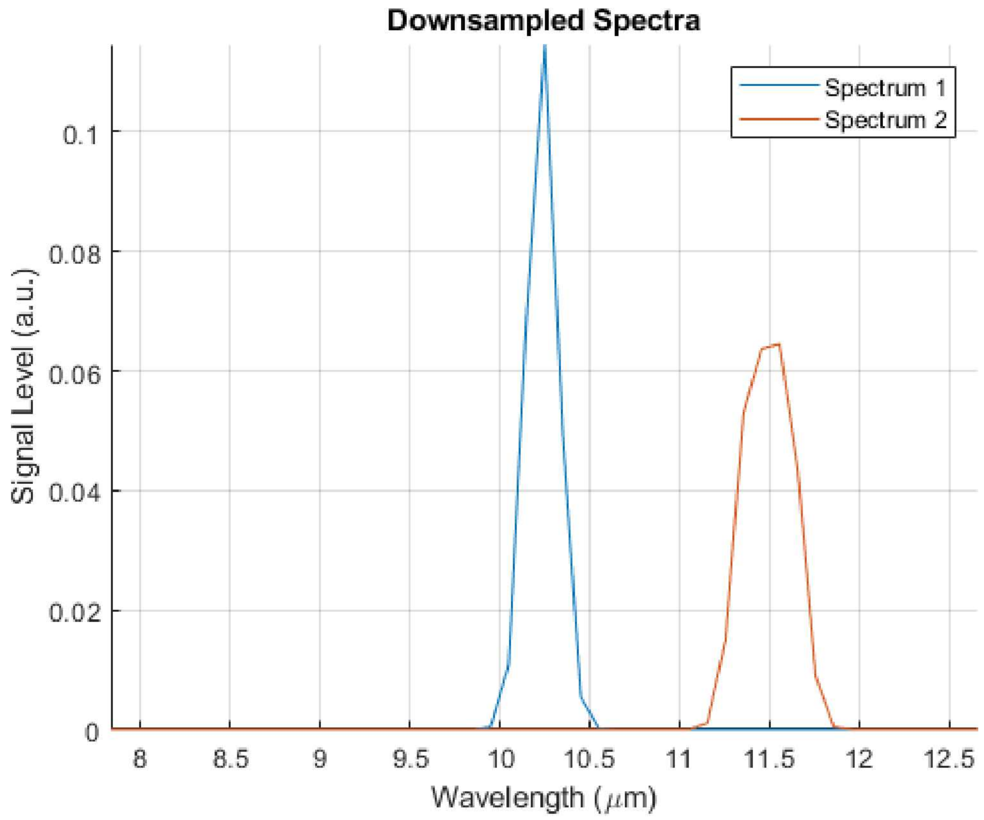
- The spectra are shown here with 196 samples across the pass-band.

Spectral Super-Resolution: CSSIS Measurements

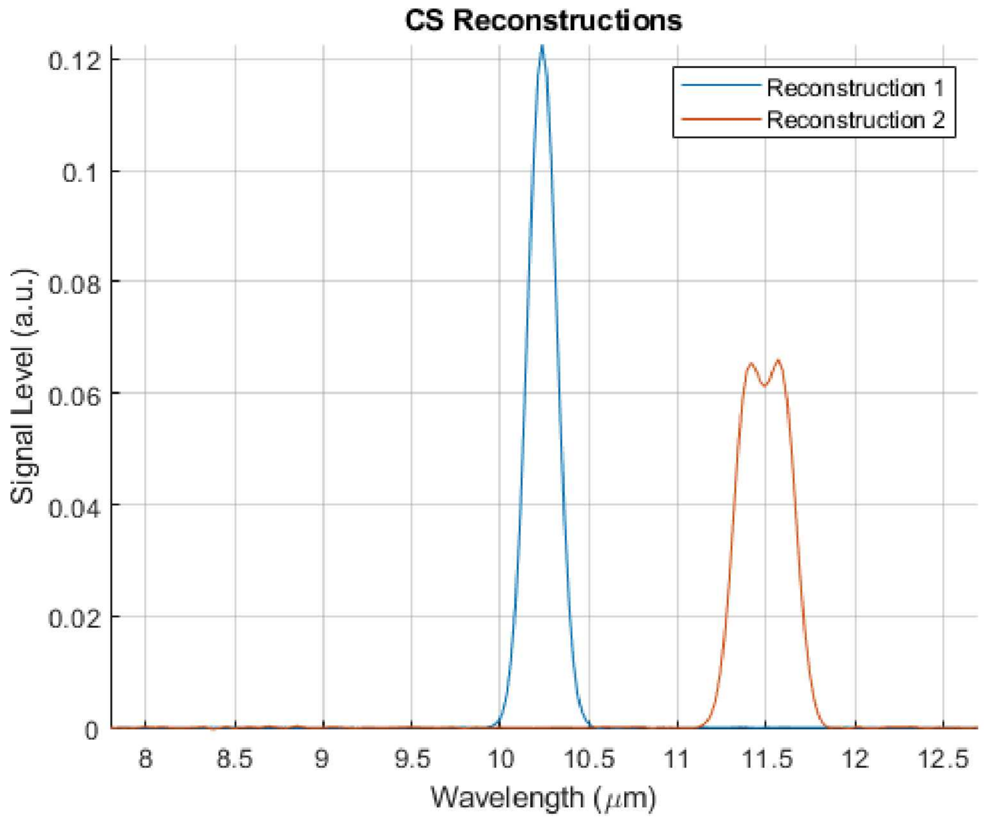


- The signal level for each of the 49 Fabry-Perot filters is shown for each spectrum.
- Measurement 1 corresponds to the response seen for Spectrum 1.
- Measurement 2 corresponds to the response seen for Spectrum 2.

Spectral Super-Resolution: Results



Traditional Spectrometer Spectra



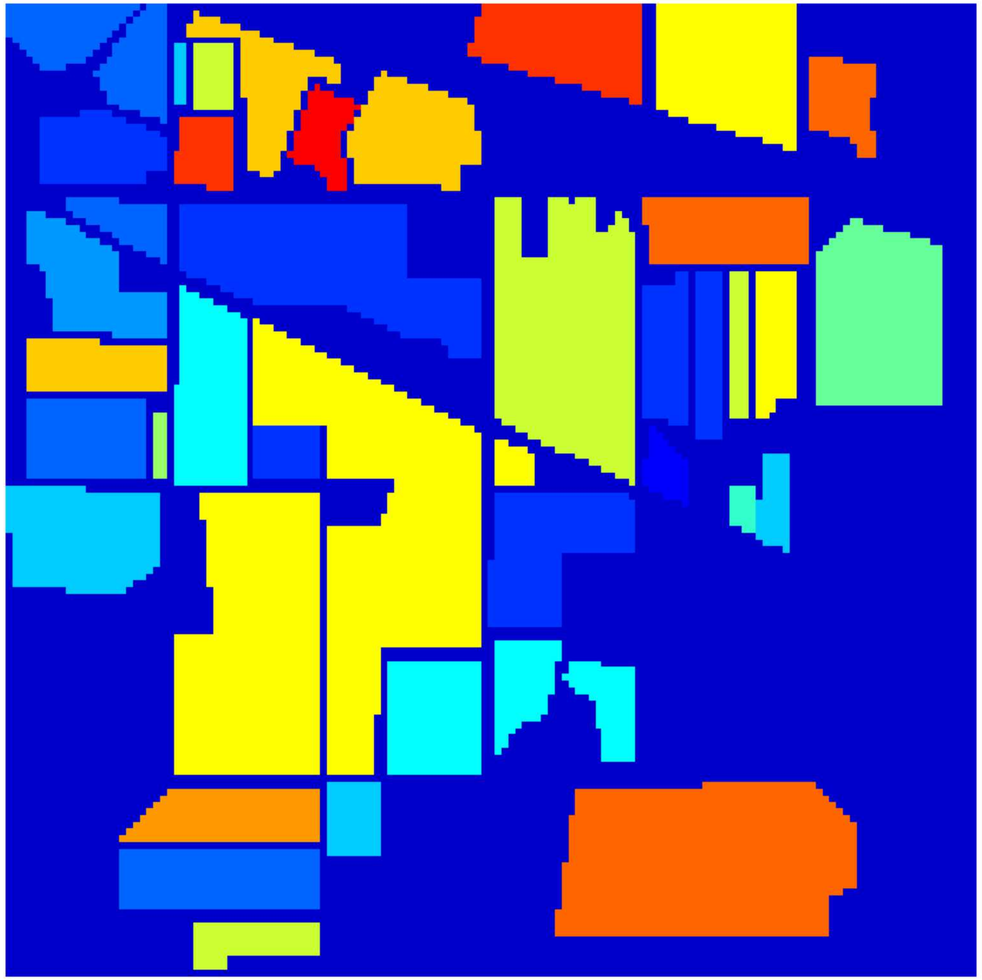
CSSIS Reconstructed Spectra

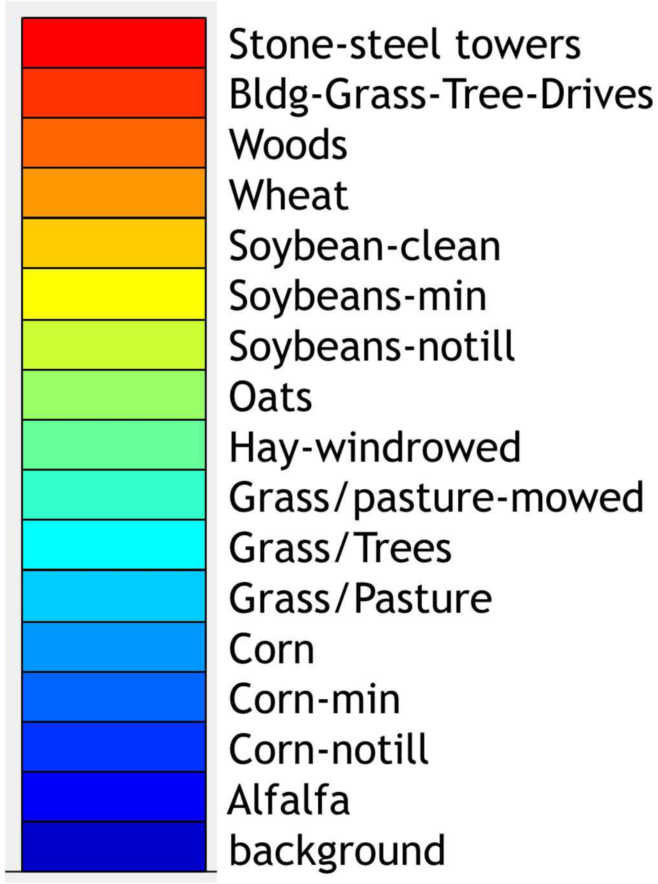
- The traditional spectrometer does not have sufficient resolution to sense the peaks in Spectrum 2.
- With the same number of measurements, the CSSIS can reconstruct these peaks.

Spectral Classification

- Question: How does the performance of a classification task for the CSSIS compare to that of the traditional tiled array spectrometer?
- For this, real-world spectra were simulated along with a radiometrically-accurate sensor model.
- The Indian Pines data set was used to generate 17 spectra for a classification study.
- The Indian Pines data set is a 145x145 hyperspectral image collected over the Purdue University agronomy farm in West Lafayette, Indiana.
- The spectrometer was AVIRIS (Airborne Visible/Infrared Imaging Spectrometer).
  - 220 spectral bands from 0.4 to 2.5 μm.
- For each of the 17 classes, the spectral average of all members were calculated.

Spectral Classification: Indian Pines Data Set

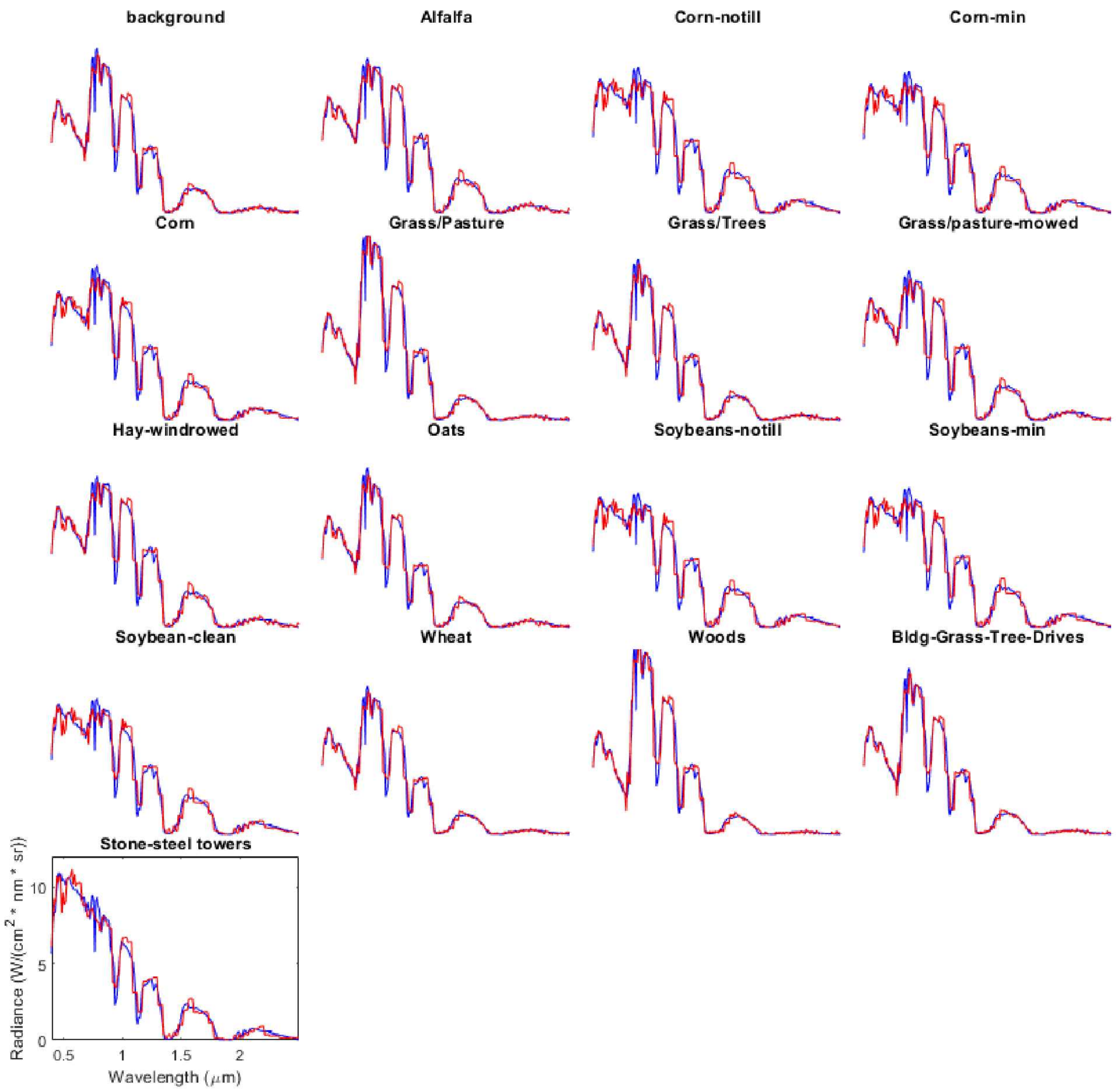




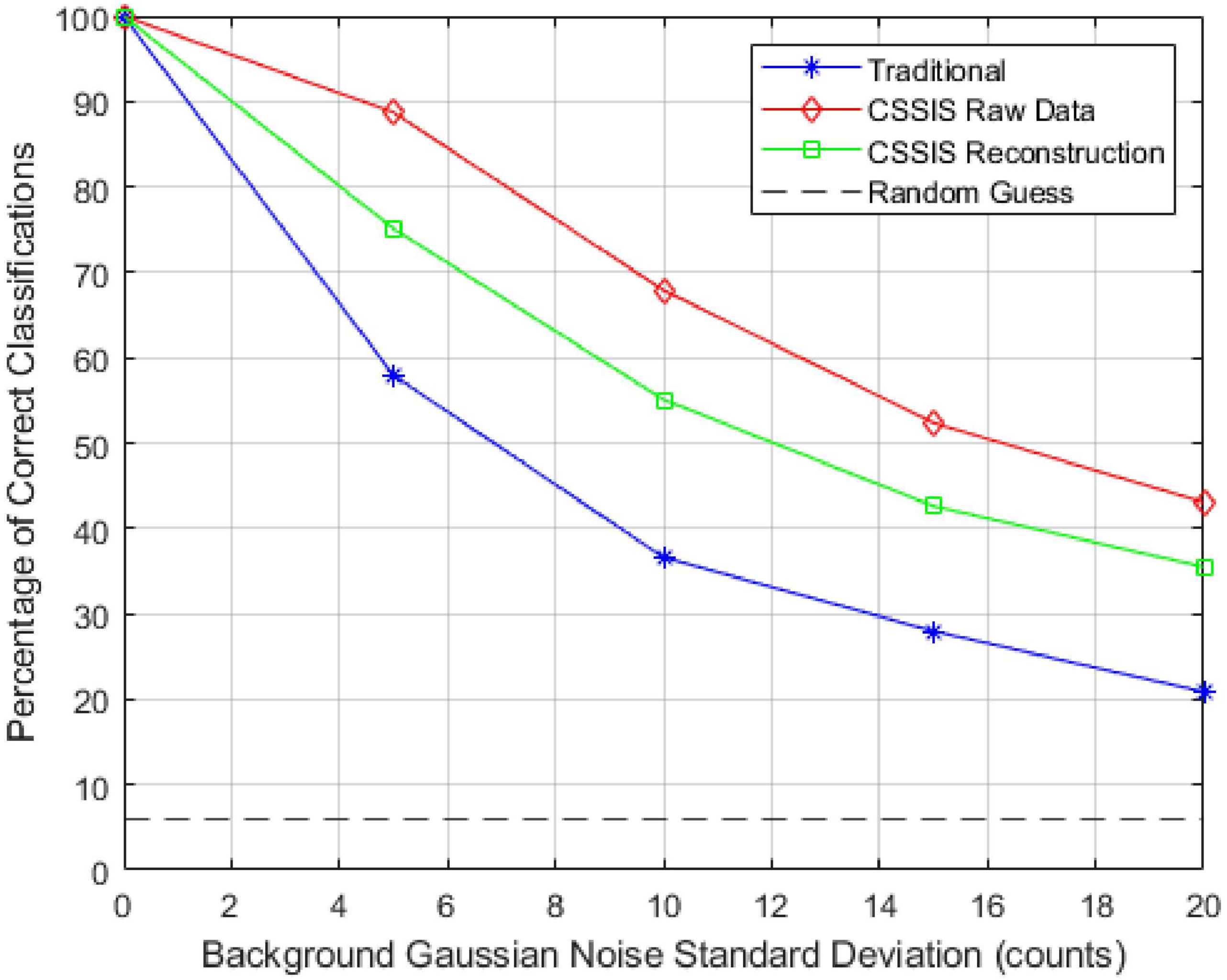
Spectral Classification

- A simulated sensor was used:
  - 12-bit analog-to-digital converter
  - Full well-depth of 100,000 electrons
  - 4 electron read-noise
- For the traditional spectrometer, ideal non-overlapping filters with unity transmittance were simulated.
- For the CSSIS, LCDs were simulated.
  - The LCD voltages were determined via an optimization to minimize the coherence of the sensing matrix.
  - Reconstruction was performed by minimizing the total variation of the Haar wavelets.
- Gaussian background noise was assumed present as well.
- For each spectral class, 1,000 measurements were simulated with 70% used for training and 30% used for testing.
- A simple k-Nearest Neighbor classifier was used.

Spectral Classification: Reconstructions



Spectral Classification: Results



- The classification task performs best on the CSSIS data in its raw form.
- The classification task performs worst on the data collected with the traditional spectrometer.

Summary

- Compressive sensing (CS) techniques are finding utility in a wide range of sensing modalities, including spectroscopy.
- By appropriately designing filters, a tiled array spectrometer can be combined with CS principles to design a snapshot imaging spectrometer.
- This spectrometer has the potential to significantly impact the trade between spectral resolution, spatial resolution, and field-of-view.
- Machine learning tasks can be more successful when operating on the CS data in its raw form, especially when noise is present.
- By performing the tasks in this domain, benefits such as increased speed and reduced computational requirements can be realized.
- The paper associated with this presentation includes other results not presented here.
  - Reconstruction performance of the CSSIS with spatial variations in the input spectrum is analyzed.
  - Classification performance on the Indian Pines data set with real-world intraclass variation is presented.