STATISTICAL TESTS FOR HYPERSPECTRAL CODED ACQUISITION ANALYSIS

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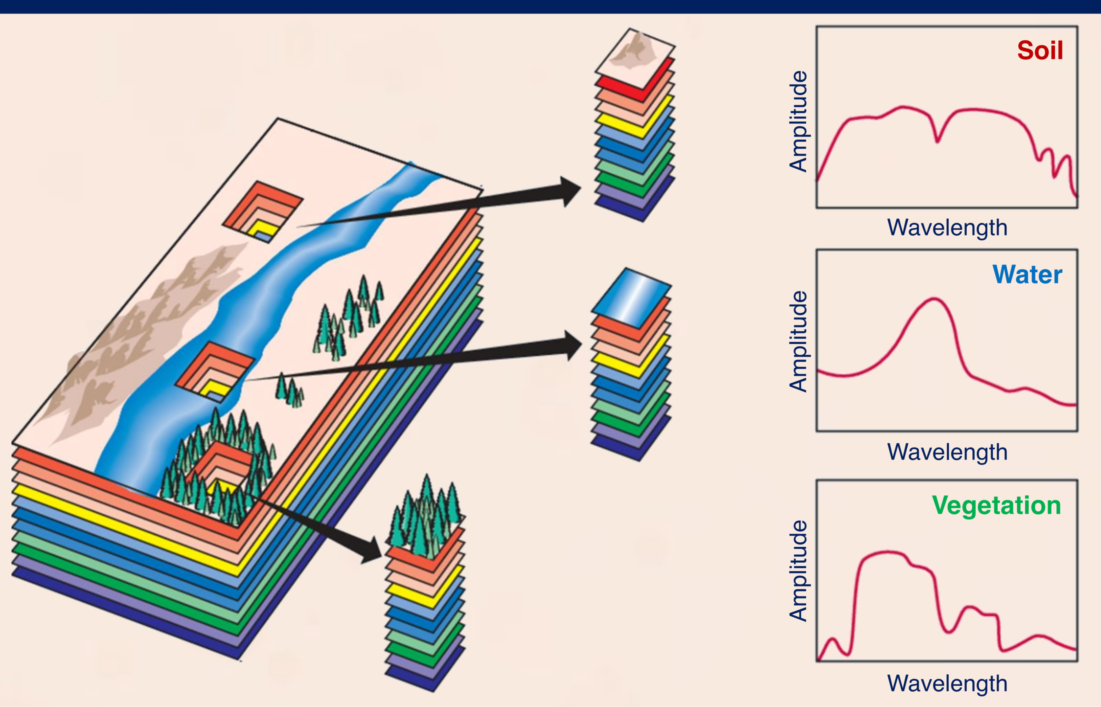
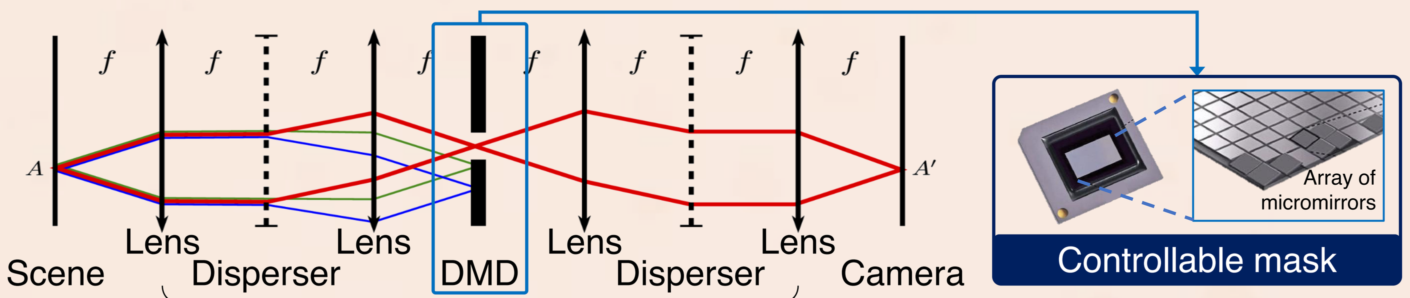
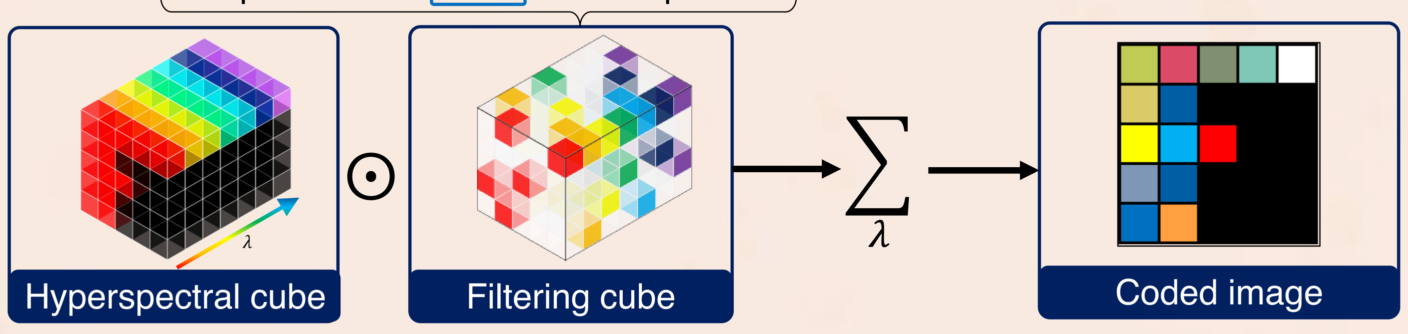
Abstract: Co-designed and programmable hyperspectral imagers use computational imaging to reduce acquisition time of hyperspectral scenes. They rely on measuring one or a few coded images and using a model to estimate the hyperspectral scene, reducing data and acquisition time. The accuracy of the estimation depends on the adequacy of the model to the observed scene. In this study we examine a separability assumption of the scene over homogeneous regions and verifies the model using statistical tests from the coded data.

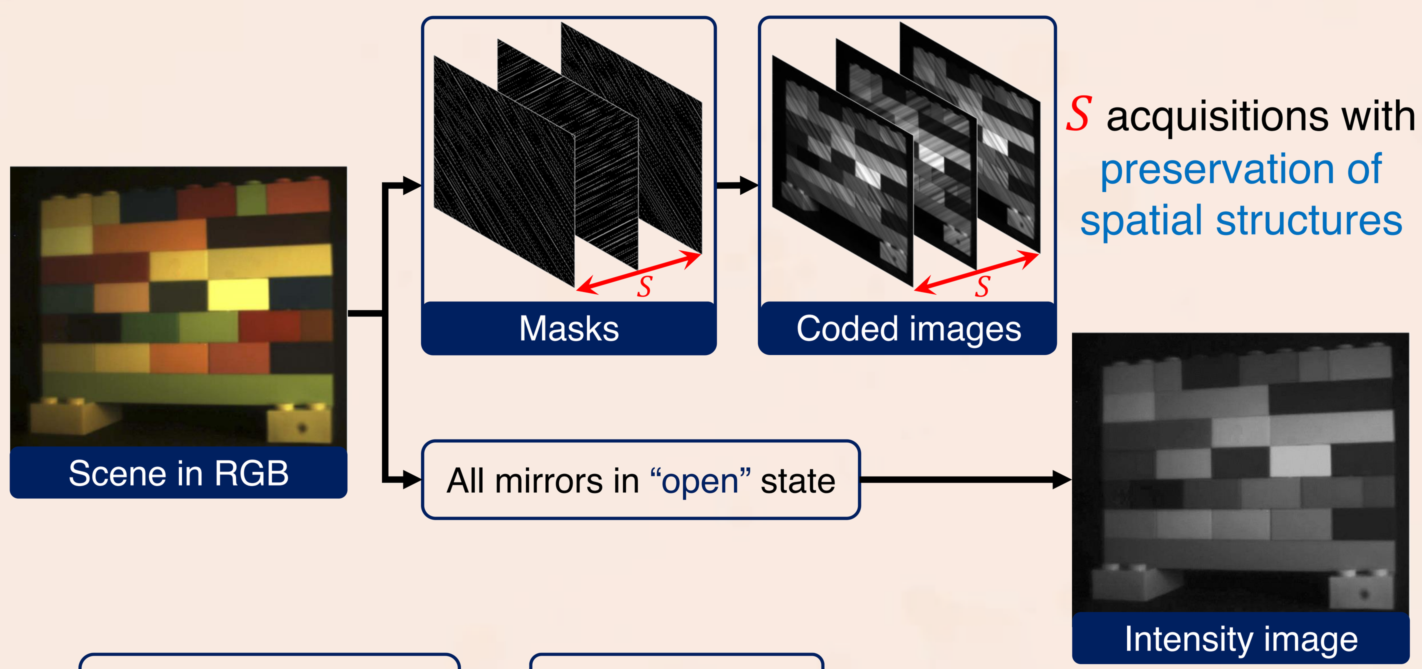
1. Hyperspectral imaging



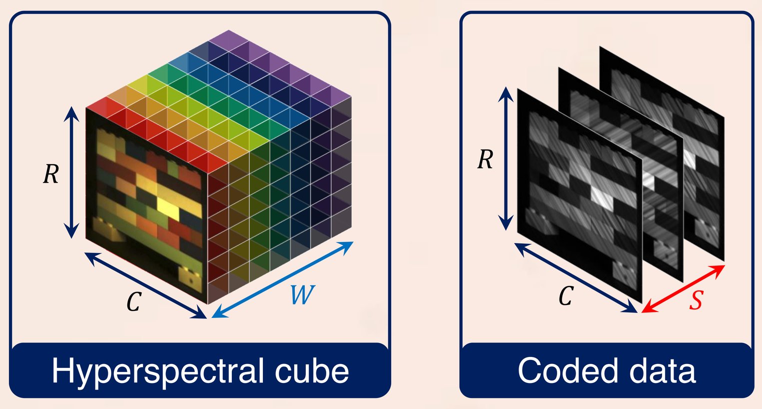
2. Coded data acquisition by DD-CASSI(*) [1]







S acquisitions with preservation of spatial structures



$S \ll W$

- Acquisition time ↓
- Data volume ↓
- SNR ↑

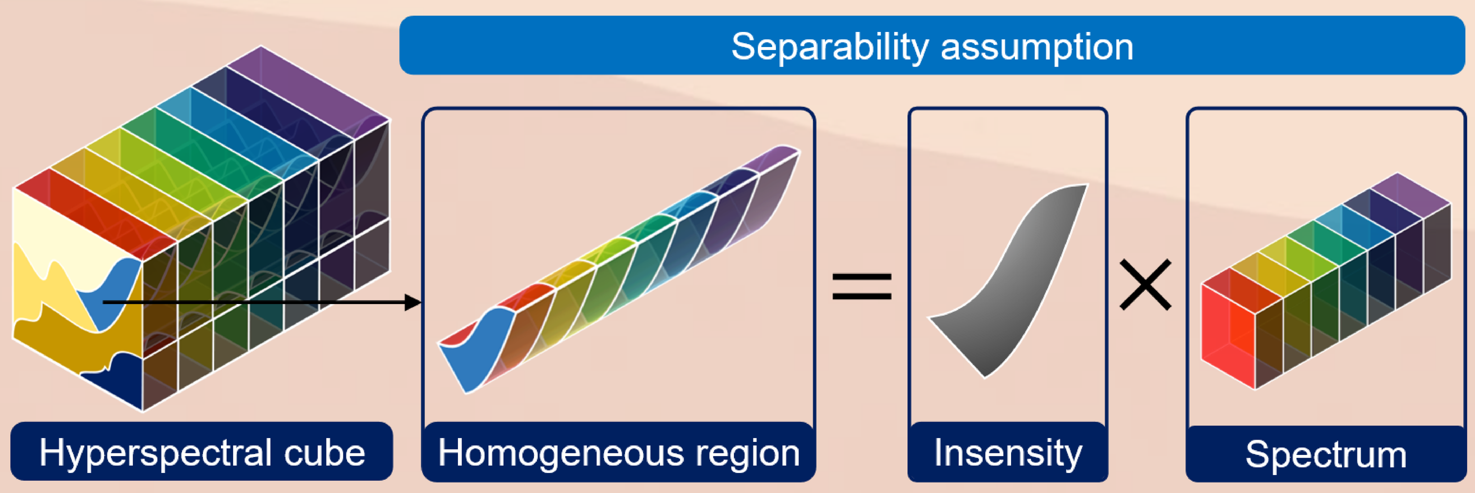
Coded data acquisition model

$$\mathbf{d} = \mathbf{H}\mathbf{o} + \mathbf{b}$$

Coded data ($\mathbf{d}$), Filtering cube ($\mathbf{H}$), Hyperspectral cube ($\mathbf{o}$), Noise ($\mathbf{b}$)

(*) Double Disperser Coded Aperture Snapshot Spectral Imager

3. Reconstruction by SA(**) method [2]



✓ Quick and easy

× Reconstruction quality depends on segmentation

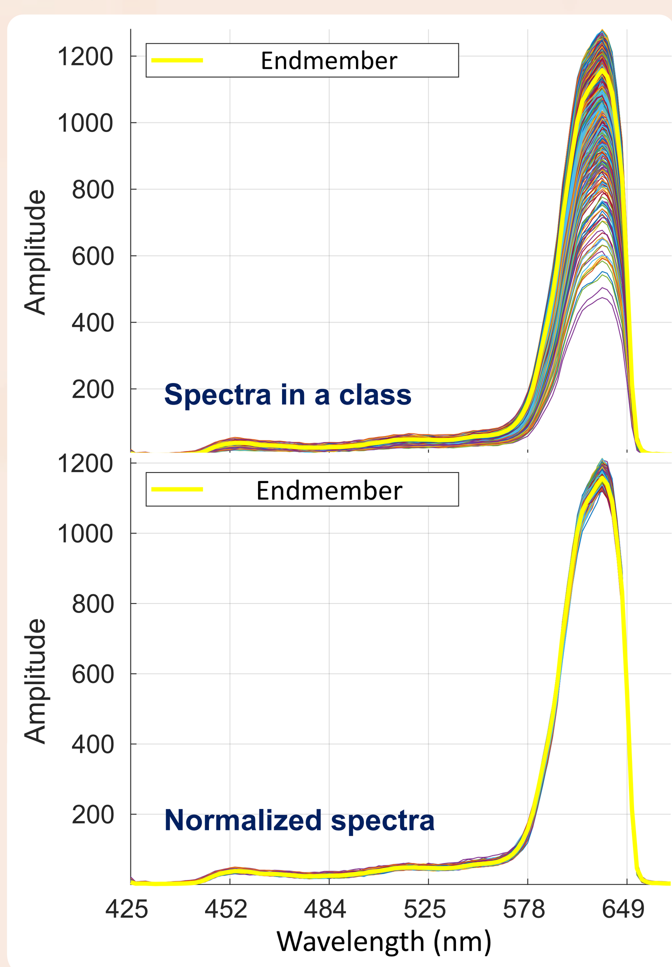
✓ Majority of the scene : well reconstructed

× Small regions or isolated pixels : correction required

→ Reallocating : supervised classification type approach with reference spectra ← large homogeneous regions

(**) Separability Assumption

4. Intraclass spectral variability



Linear approximation of the Hapke model on the intraclass spectral variability [3] :

$$\mathbf{o}_n = \psi_n \bar{\mathbf{s}}$$

n^{th} hyperspectral pixel ($\mathbf{o}_n$), Reference spectrum ($\bar{\mathbf{s}}$), Variability coefficient (ψ_n)

Estimation of ψ_n:

- from coded data:

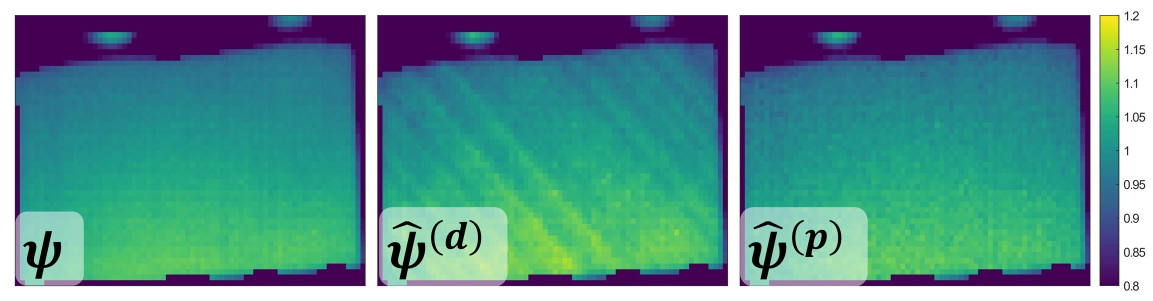
$$\hat{\psi}_n^{(d)} = (\bar{\mathbf{s}}^T \mathbf{H}_n^T \mathbf{H}_n \bar{\mathbf{s}})^{-1} \bar{\mathbf{s}}^T \mathbf{H}_n^T \mathbf{d}_n$$

($\mathbf{d}_n$: n^{th} pixel of coded data)

- from panchromatic image:

$$\hat{\psi}_n^{(p)} = (\mathbf{1}^T \bar{\mathbf{s}})^{-1} p_n$$

(p_n: n^{th} pixel of panchromatic image)



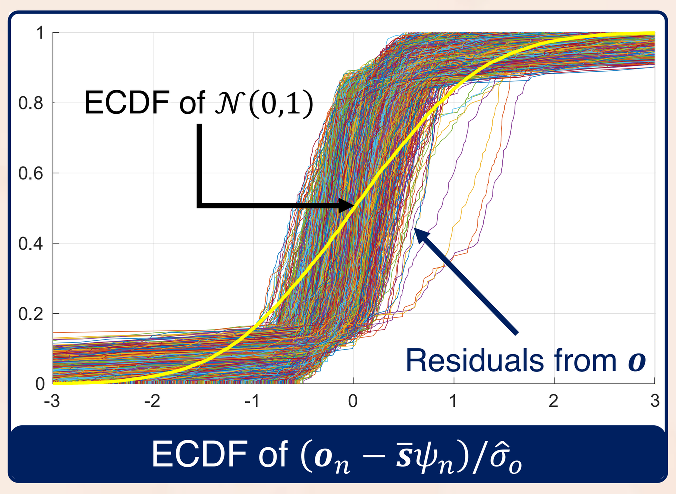
5. Noise model & statistical analysis

Detector noise ~ Poisson law :

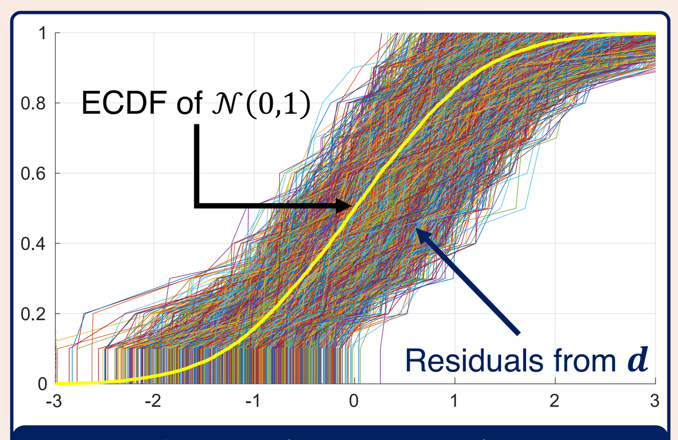
- ≈ Gaussian additive noise for high flux
- Stationarity for low flux variations

× Unlikely on $\boldsymbol{o}_n$: high flux variation across isolated spectral bands.

✓ More likely on $\boldsymbol{d}_n$: sum of several spectral bands reduces flux variations.

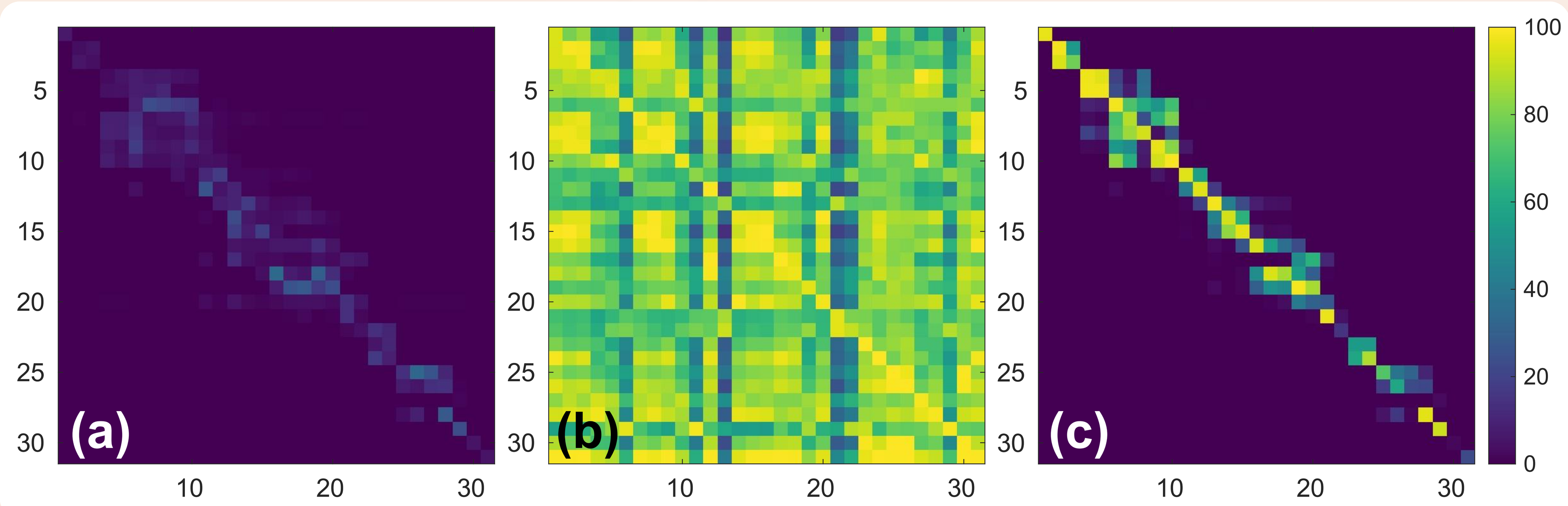


ECDF of $(o_n - \bar{s}\psi_n)/\hat{\sigma}_o$



ECDF of $(\boldsymbol{d}_n - \mathbf{H}_n \bar{s}\psi_n)/\hat{\sigma}_d$

6. Validation by statistical tests



Percentages map of validation of the KS test on the residuals: (a) without variability, (b) $\hat{\psi}_n^{(d)}$, (c) $\hat{\psi}_n^{(p)}$

Using statistical test to:

- Validate our variability assumptions and our noise model
- Detect if we assign an erroneous reference spectrum to a pixel.

→ Kolmogorov-Smirnov test with hypothesis $\mathcal{H}_0 : \boldsymbol{r}_n / \hat{\sigma} \sim \mathcal{N}(0,1)$.

$$\boldsymbol{r}_n^{k,\ell} = \boldsymbol{d}_n^k - \mathbf{H}_n \bar{\boldsymbol{s}}^\ell \psi_n^\ell$$

$\boldsymbol{d}_n^k$: n^{th} pixel of coded data of class k; $\bar{\boldsymbol{s}}^\ell$: Reference spectrum of class ℓ

Desired results:
- $\ell = k$: accepted at 95%
- Other cases: rejected

Obtained results:

- Neglecting the variability (a) or using $\hat{\psi}_n^{(d)}$ (b): not satisfactory.
- Using $\hat{\psi}_n^{(p)}$ (c): rather satisfactory, except
  - classes with similar reference spectrum
  - low SNR data

References

[1] Single-shot compressive spectral imaging with a dual-disperser architecture, M. E. Gehm et al., Oct 2007

[2] Optimized coded aperture for frugal hyperspectral image recovery using a dual-disperser system, E. Hemsley, I. Ardi et al., Nov 2020

[3] Endmember Variability in hyperspectral image unmixing, L. Drumetz, PhD thesis, Oct 2016