

#### **Hierarchical Compressed Subspace Clustering of Infrared Single-pixel Measurements**



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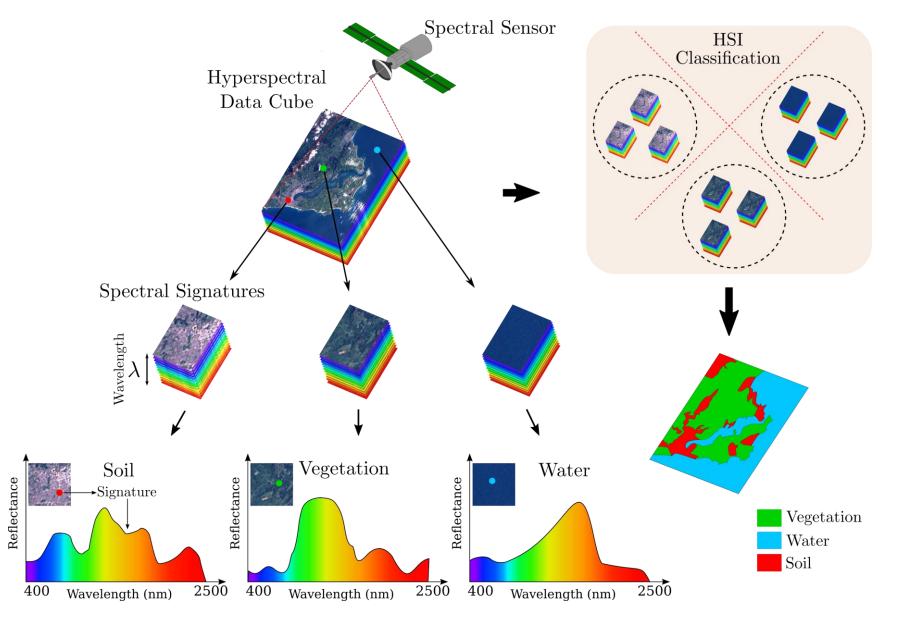
**Karen Sanchez** 



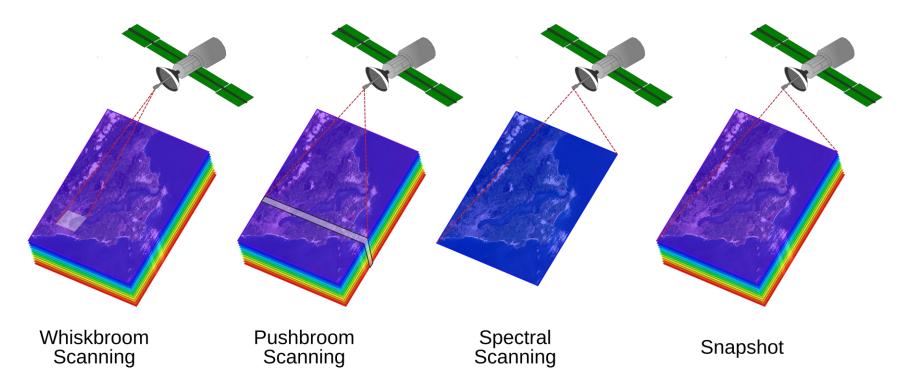
Carlos Hinojosa



#### **HSI Clustering**

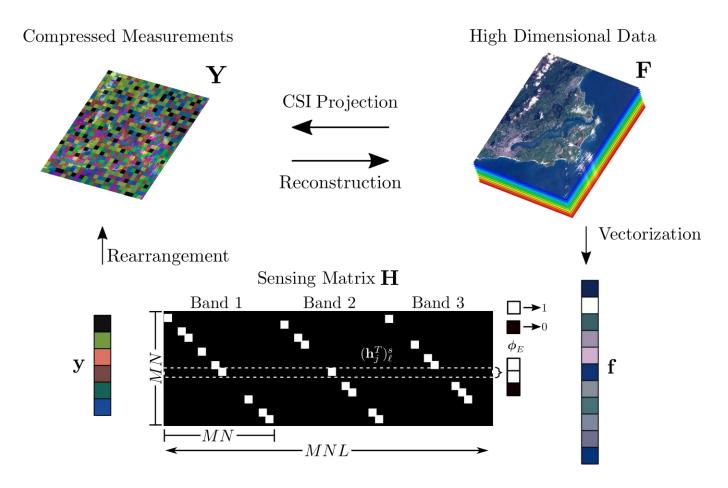


#### Hyperspectral imaging



- Traditional hyperspectral imaging techniques relies on Nyquist-Shannon sampling theorem.
- Require a fixed sampling rate along the three dimensions, leading to a large amount of captured data and large acquisition times.

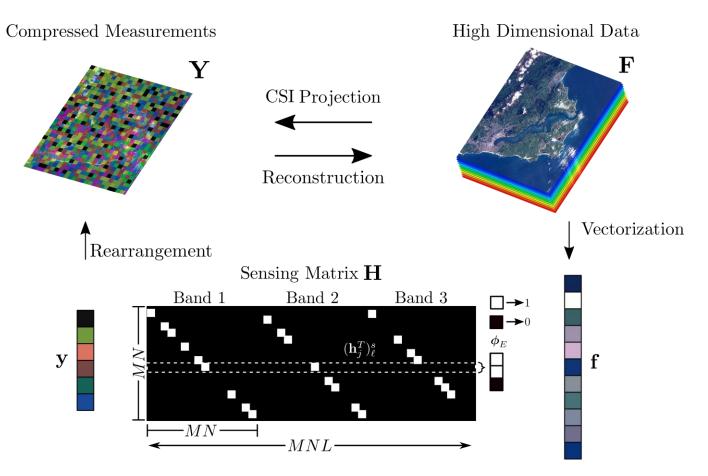
## **Compressive Spectral Imaging (CSI)**



- Senses and simultaneously reduces the data dimension without any further processing step.
- Captures less samples than traditional methods.
- Assumes that f can be represented as a sparse vector  $\theta$  in some basis

 $\Psi$ , i.e,  $\mathbf{f} = \Psi \boldsymbol{\theta}$ .

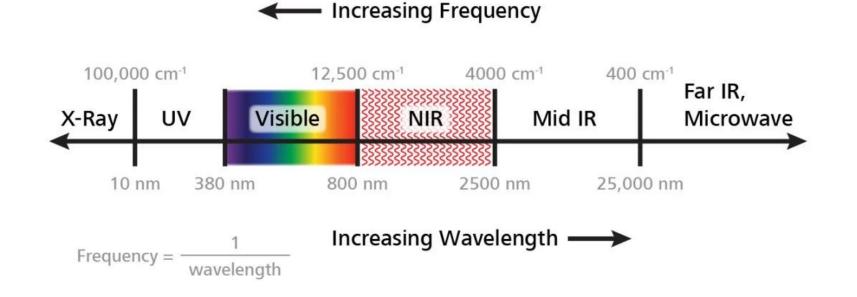
### **Compressive Spectral Imaging**



- Then, the acquisition process can be modeled as y = Hf, where H is the sensing matrix of the system.
- Using **g** and taking advantage of sparsity of **f**, the original full HSI can be recovered as

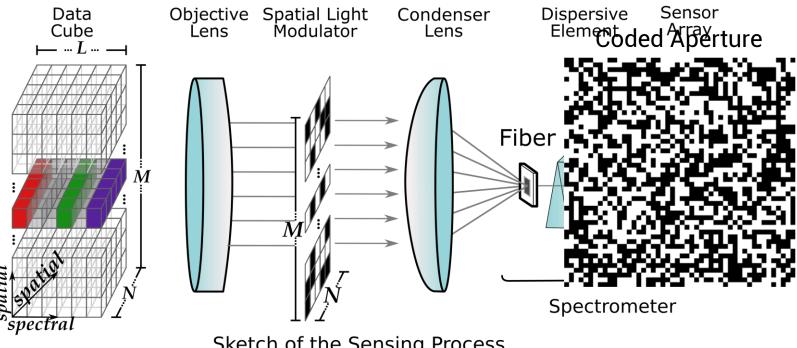
$$\mathbf{\hat{f}} = \mathbf{\Psi} \left\{ rgmin_{oldsymbol{ heta}} \| \mathbf{H} \mathbf{\Psi} oldsymbol{ heta} - \mathbf{g} \|_2^2 + \lambda \| oldsymbol{ heta} \|_1 
ight\}$$

#### From visible spectrum to NIR



- Traditionally the scenes are acquired inside the visible spectrum range, i.e., beginning at 400 nm.
- This paper develops a clustering approach to obtain unsupervised pixel classification directly from the compressive infrared single-pixel camera (SPC) domain (900 - 2500 nm).

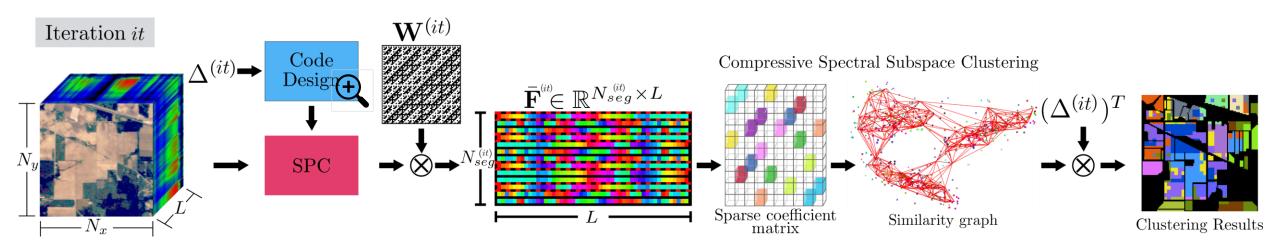
#### Single pixel camera



Sketch of the Sensing Process

SPC architecture excels due to its low implementation cost when acquiring a large • number of spectral band.

#### **Proposed Method**



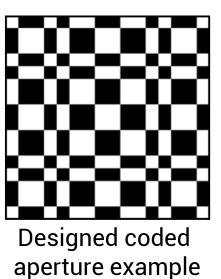
### **Downsampling Matrix Design**

| Algorithm 1 Downsampling Matrix Design   |  |
|--|--|
| Require: $N_{seg}, \bar{\mathbf{F}}$   |  |
| Ensure: $\Delta$   |  |
| 1: <b>procedure</b> DSAMPLING_DESIGN( $\overline{\mathbf{F}}$ )                      | $, N_{seg})$                                 |
| 2: $k_{idx} \leftarrow \text{RegularSegms}(\bar{\mathbf{F}}, N_{seg})$               | $\triangleright k_{idx}$ contains the        |
| segment labels   |  |
| 3: $\Delta \leftarrow \operatorname{zeros}(N_{seg}, \operatorname{length}(k_{idx}))$ |  |
| 4: <b>for</b> $e \leftarrow 1$ to $N_{seg}$ <b>do</b>                                |  |
| 5: $\mathbf{p}^e \leftarrow \operatorname{find}(k_{idx} = e)$                        |  |
| 6: $n_e \leftarrow \text{length}(\mathbf{p}^e)$                                      |  |
| 7: <b>for</b> $j \leftarrow 1$ to $n_e$ <b>do</b>                                    |  |
| 8: $ (\delta_e)^T_{(\mathbf{p}^e)_i} = \frac{1}{n_e} $                               | $\triangleright$ Update each row of $\Delta$ |
| 9: end for   |  |
| 10: <b>end for</b>   |  |
| 11: <b>return Δ</b>  |  |
| 12: end procedure  |  |

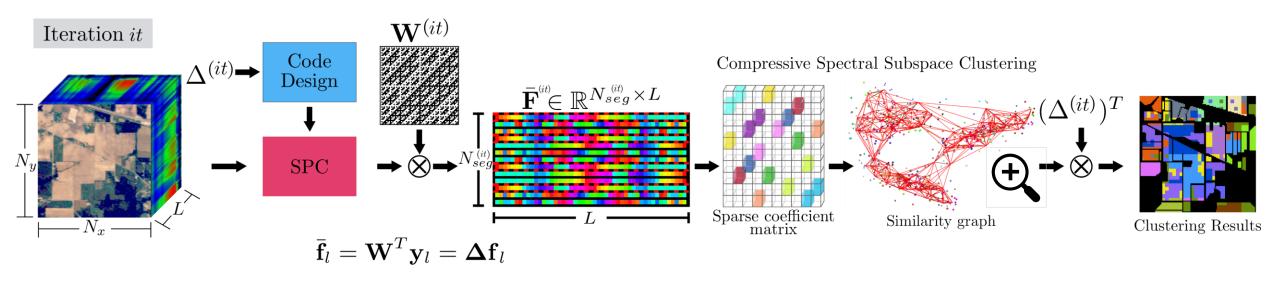
 $\mathbf{H}=\mathbf{W}\mathbf{\Delta}$  $\mathbf{W}\in\{-1,1\}^{K imes K}$ Hadamard Matrix

$$\mathbf{\Delta} \in \mathbb{R}^{N_{seg} imes MN}$$
 — Decimation matrix

$$\tilde{\mathbf{f}}_l = (1/K) \mathbf{\Delta}^T \mathbf{W}^T \mathbf{y}_l = (1/K) \mathbf{\Delta}^T \mathbf{W}^T \mathbf{W} \mathbf{\Delta} \mathbf{f}_l \approx \mathbf{f}_l$$



#### **Proposed Method**



• Instead of performing the complete reconstructions, it is possible to directly extract features from the compressed measurements.

#### **Compressive spectral subspace clustering**

#### Algorithm 2 Data Clustering

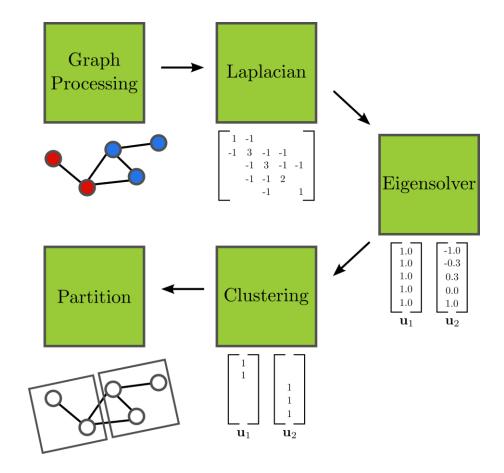
**Require:**  $\bar{\mathbf{F}} \in \mathbb{R}^{N_{seg} \times L}$ ,  $\Delta$  downsampling matrix,  $\kappa$  clusters **Ensure:** Segmentation of the spectral pixels:  $\mathbf{F}_1, \dots, \mathbf{F}_k$ **procedure** DATA\_CLUSTERING( $\bar{\mathbf{F}}, \Delta, \kappa$ )

2:  $\mathbf{G} \leftarrow \text{Build}_\text{Sim}_\text{Graph}(\bar{\mathbf{F}}) \triangleright \kappa$ -nearest neighbor graph  $\triangleright$ Obtain Cluster indices

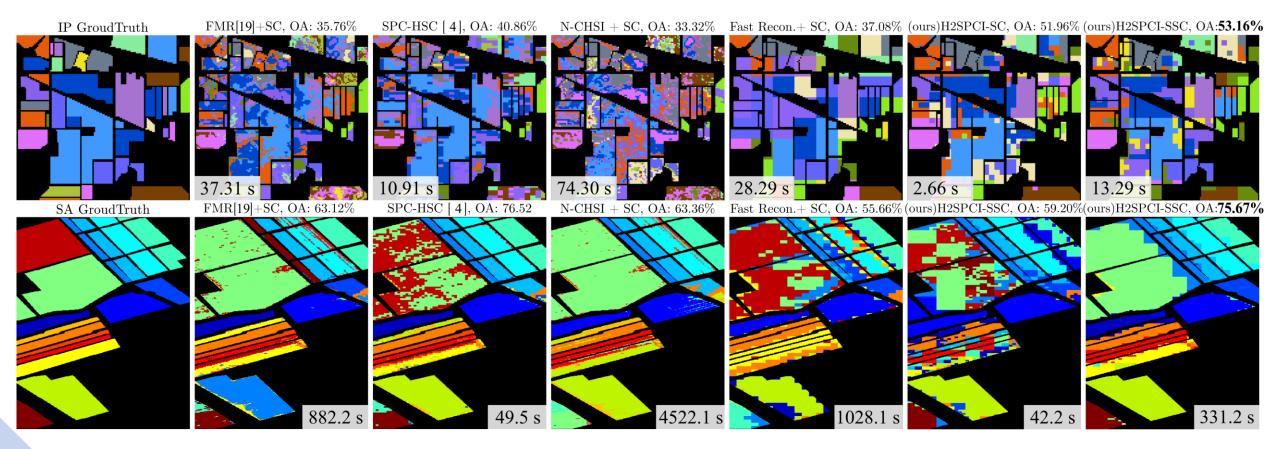
 $\bar{\mathbf{C}}_{idx} \leftarrow \text{Spectral}_{Clustering}(\mathbf{G}, \kappa) \triangleright \text{Spectral}_{Clustering}$ [19]

4:  $\mathbf{C}_{idx} \leftarrow \mathbf{\Delta}^T \bar{\mathbf{C}}_{idx}$ end procedure

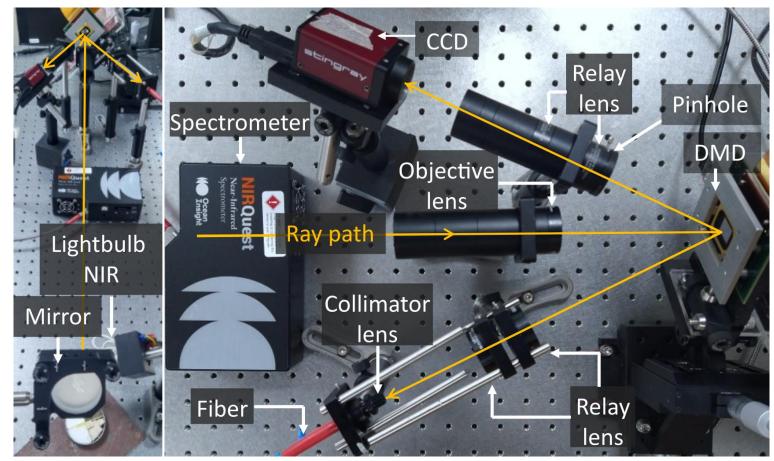
▷ Upsampling



#### **Simulations**



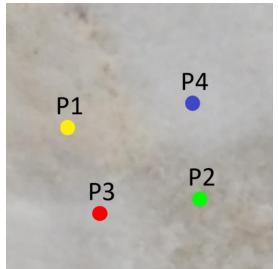
#### **Experimentation**



**Experimental Setup** 

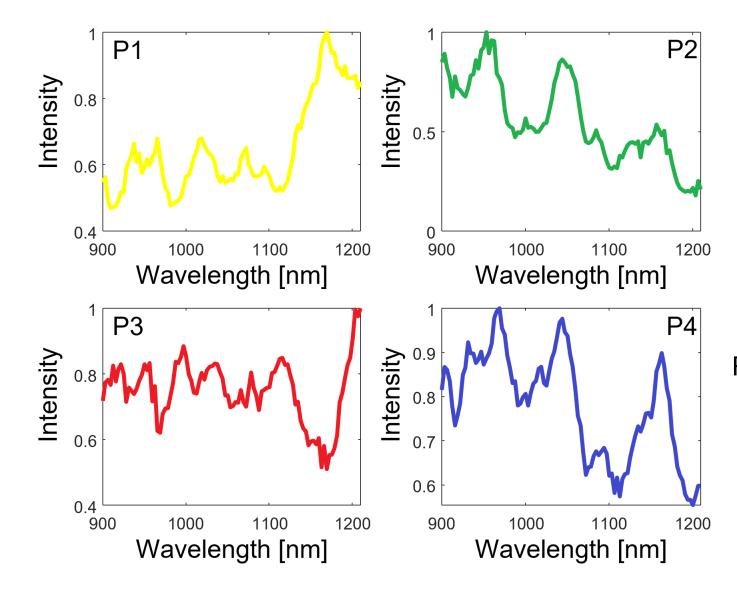


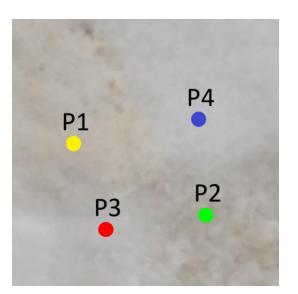
#### False RGB composite



RGB composite acquired with a traditional camera

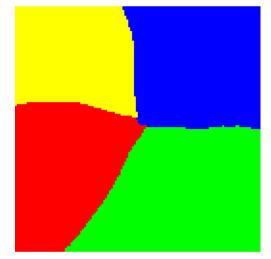
#### **Experimentation**



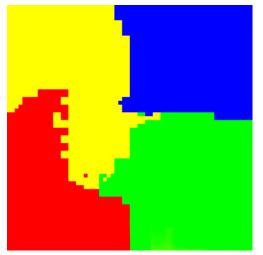


RGB composite acquired with a traditional camera

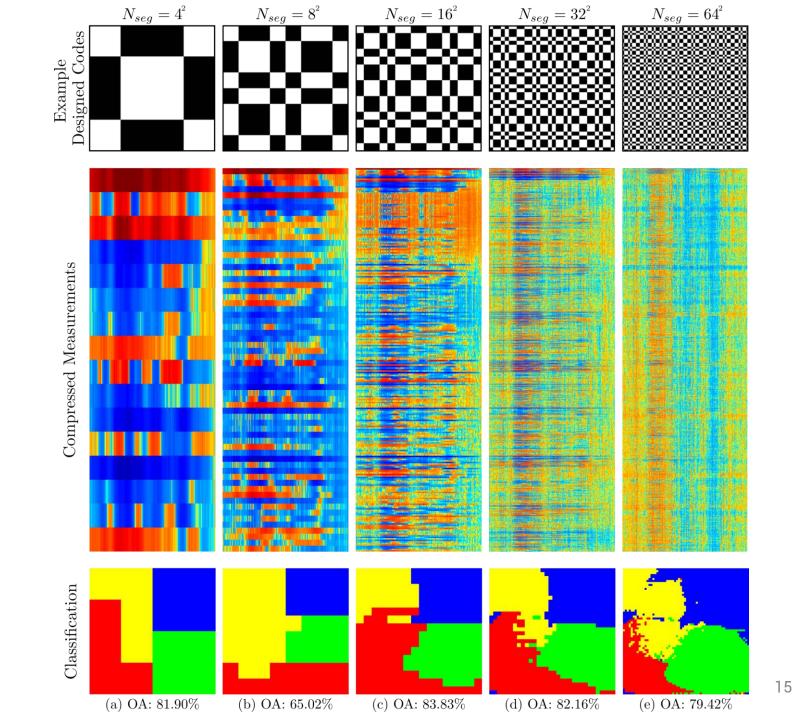
#### Experimentation



Ground truth

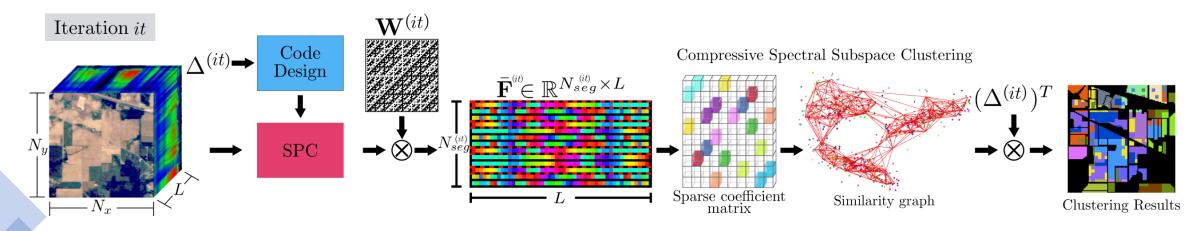


Final classification result via majority voting. OA: 85%



#### Conclusions

- The main contribution presented in this document is the alternative to spectral clustering in CSI measurements only using the NIR spectrum and excluding the information from the traditional visible range
- This work presented a sensing matrix designed to extract features directly from the compressed measurements in each stage of the hierarchical model.
- We demonstrate that the proposed imaging system, together with the sensing protocol and the computational algorithm, represents an efficient alternative to estimate clustering maps without requiring the full HIS recovery.



# Thank You!



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Società Italiana di Spettroscopia NIR





