CREATIS Medical Imaging Research Laboratory

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Reproducible Hyperspectral Single-Pixel Imaging using the OpenSpyrit Ecosystem

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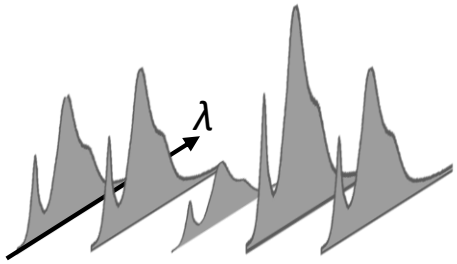
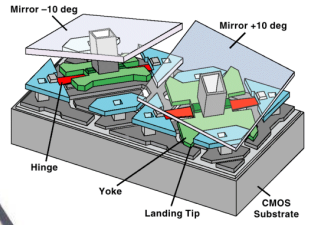
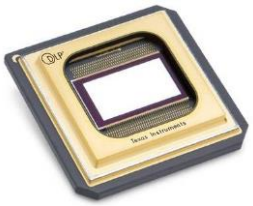
Joint work with: JFJ Abascal, T Baudier, L Mahieu-Williame

Single-Pixel Hyperspectral Imaging

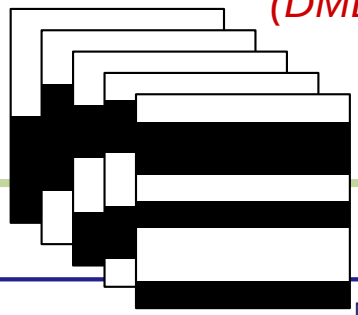


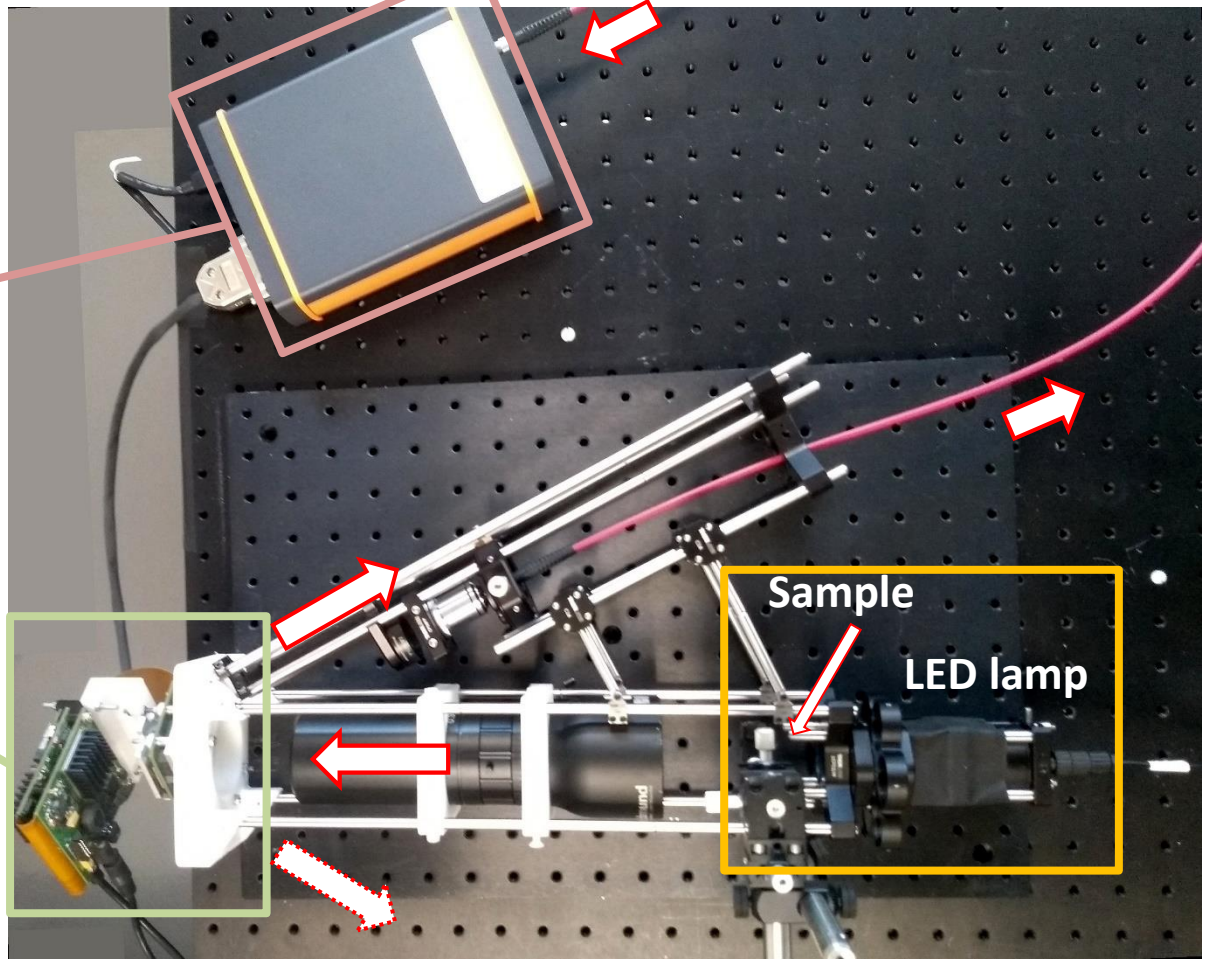
Spectrometer





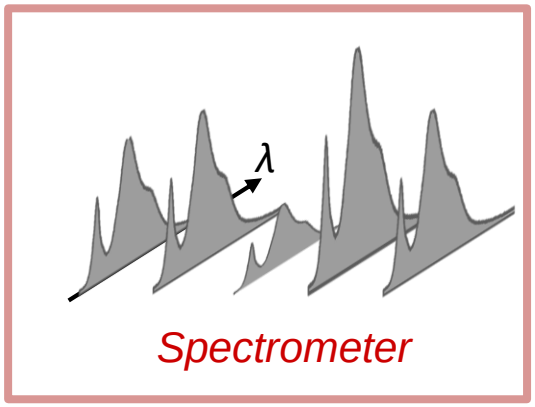
Digital Micromirror Device (DMD)

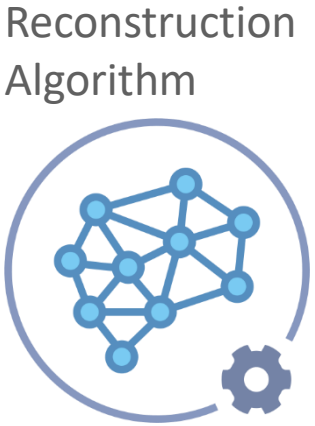


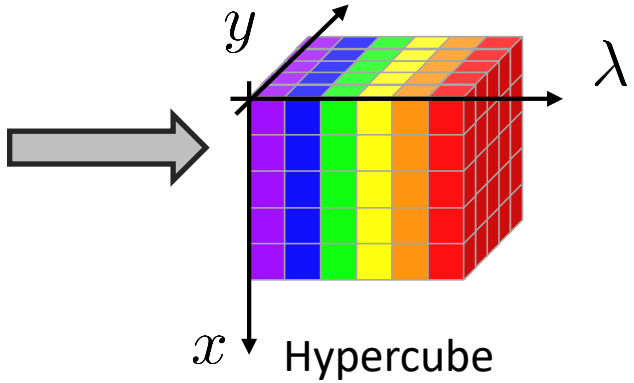


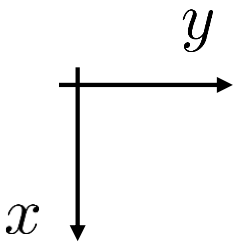
[G. Beneti *et al*. *Opt Express* **31,** 15599 (2023)]

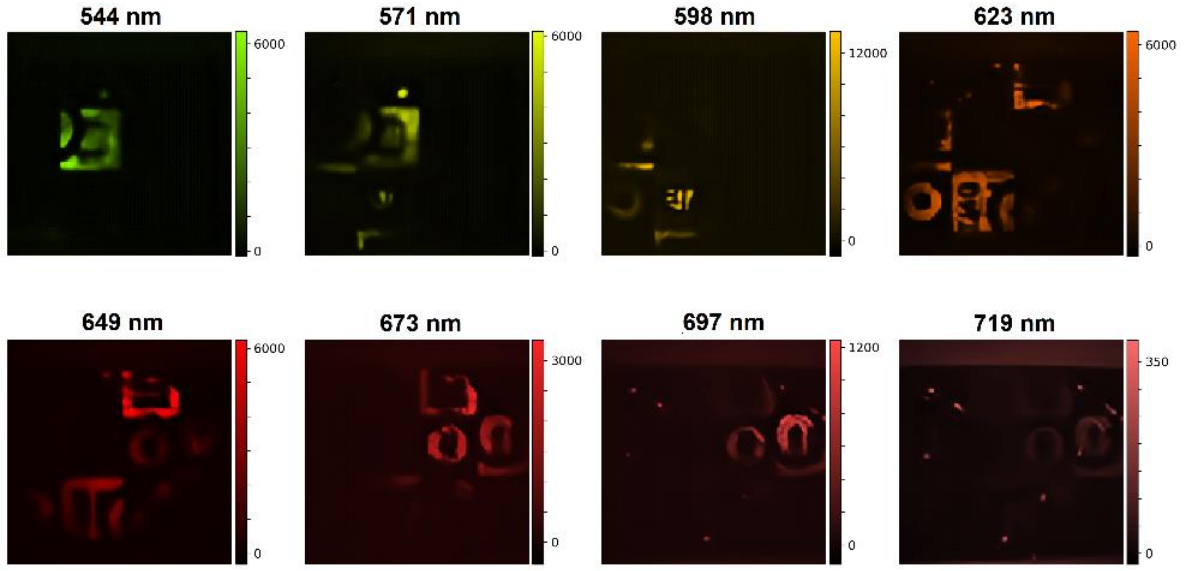
Single-Pixel Hyperspectral Imaging



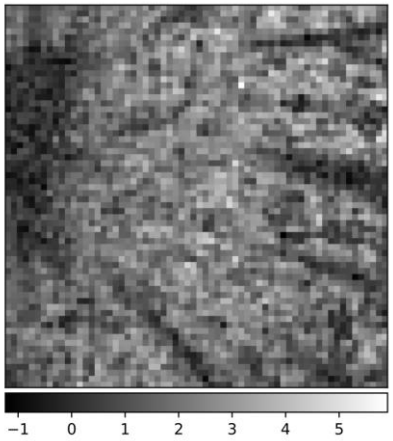
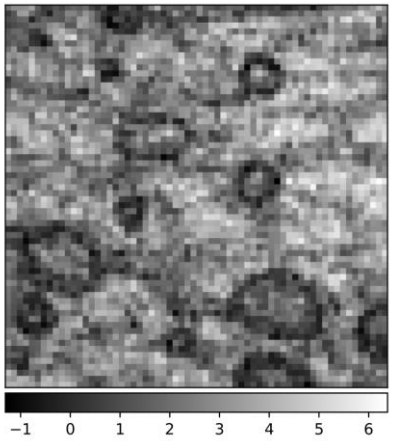
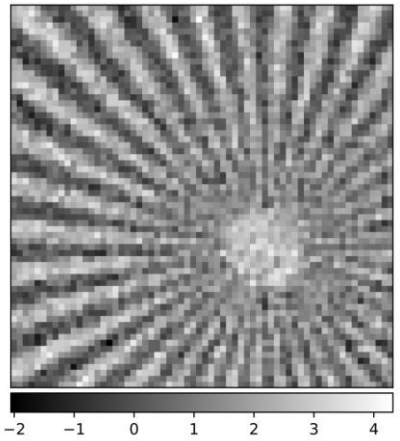
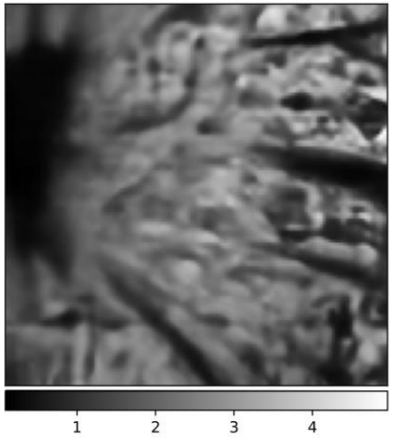
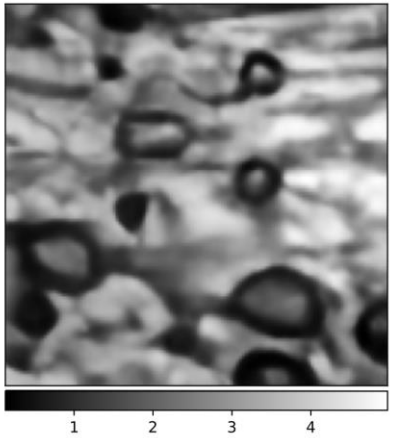
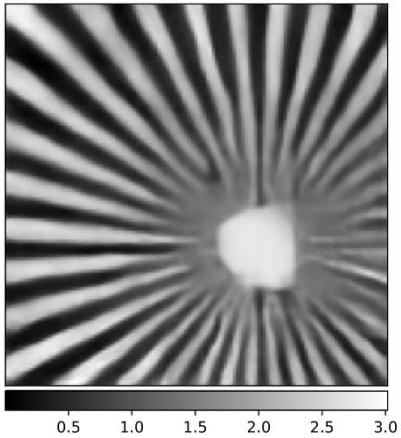








Data-driven (‘Deep’) Reconstruction

	Tomato (x1 zoom)	*Tomato (x12 zoom)*	*Star Sector (x12 zoom)*
Standard Recon			
Deep Recon			

[G. Beneti *et al*. *Opt Express* **31,** 15599 (2023)]

The Reproducibility Crisis

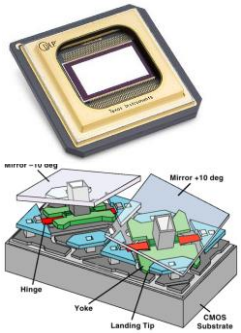
'(…) when attempting to reproduce computational results (…) from an article published just months prior, even the original authors of the experiment were unable to completely reproduce the results.'

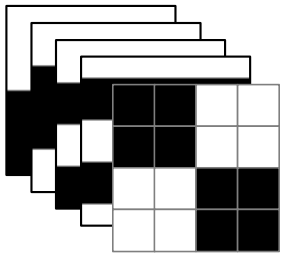
[J. Shenouda and W.U. Bajwa. *IEEE Signal Process. Mag.* **40,** 141 (2023)]

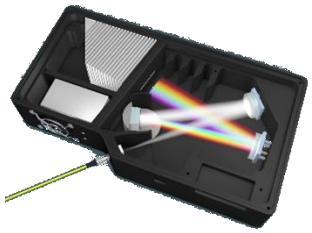
The OpenSpyrit Ecosytem

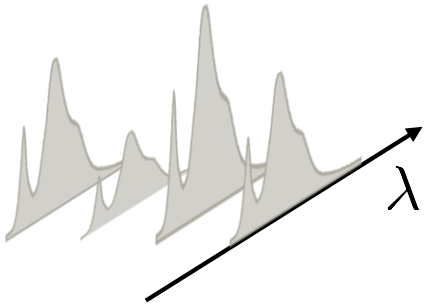
https://github.com/openspyrit/

spas

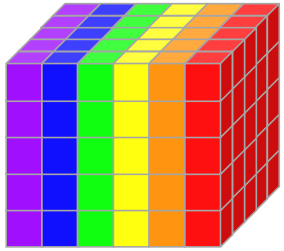




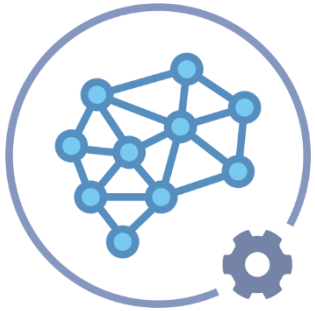




spihim



spyrit



[G. Beneti *et al*. *Opt Express* **31,** 15599 (2023)]

The SPyRiT Package

spyrit

core.meas
core.noise
core.recon

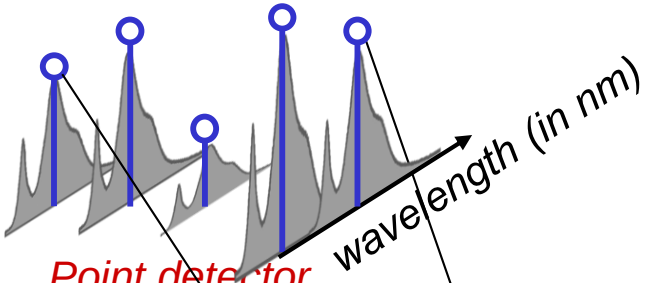
- **Available on pypi:** `pip install spyrit`
- **Source code:** https://github.com/openspyrit/spyrit/
- **Documentation:** https://spyrit.readthedocs.io/

[G. Beneti *et al*. *Opt Express* **31,** 15599 (2023)]

Single-Pixel Reconstruction (Philosophy)

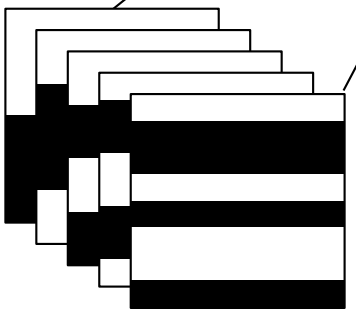
- **Linear measurements**

$$\boldsymbol{m}_\lambda = \boldsymbol{H}\,\boldsymbol{f}_\lambda$$



$$\boldsymbol{m}_\lambda = [m_{1,\lambda}, \ldots, m_{M,\lambda}]^\top \in \mathbb{R}^M$$

$$\boldsymbol{H} = [\boldsymbol{h}_1^\top, \ldots, \boldsymbol{h}_M^\top]^\top \in \mathbb{R}^{M \times N}$$



Spatial light modulator

- **Reconstruction**

Estimate $\boldsymbol{f}_\lambda$ from $\boldsymbol{m}_\lambda$

E.g., $\boldsymbol{f}_\lambda = \boldsymbol{H}^{-1}\boldsymbol{m}_\lambda$

Single-Pixel Reconstruction (in Practice)

- **Measurements are noisy**

$$\boldsymbol{m}_\lambda = g\,\mathcal{P}(\boldsymbol{H}\,\boldsymbol{f}_\lambda) + \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\sigma}^2)$$

gain — *dark current* — *dark noise*

[EMVA Standard 1288, 4.0 (2021)]

- **Accelerated acquisitions**
  - How to reduce acquisition time?

→ Limit acquisitions to a few patterns

→ This, however, degrades the image resolution!

$$M \ll N \qquad \boldsymbol{H} \qquad \boldsymbol{f}_\lambda \in \mathbb{R}^N \qquad \boldsymbol{m}_\lambda \in \mathbb{R}^M$$

Data-Driven Reconstruction Methods (1/3)

- **Learns a nonlinear 'model'**

neural network

$$\boldsymbol{f} \approx \boldsymbol{f}^* = \mathcal{G}_{\boldsymbol{\theta}^*}(\boldsymbol{m})$$

- Training phase

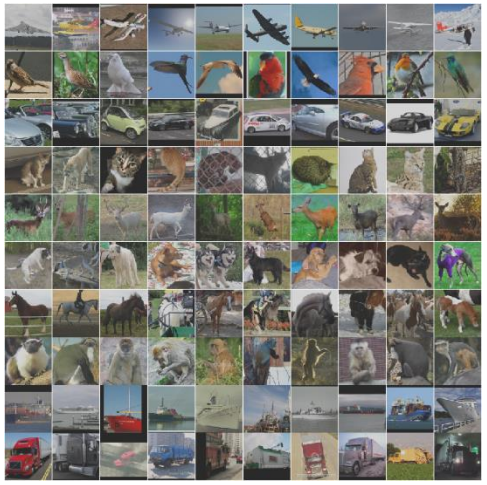
$$\boldsymbol{\theta}^* \in \arg\min_{\boldsymbol{\theta}} \frac{1}{L} \sum_{\ell} \|\mathcal{G}(\boldsymbol{\theta}; \boldsymbol{m}^\ell) - \boldsymbol{f}^\ell\|_2^2$$

  - Image-measurement pairs
  - Loss (e.g., mse)
  - Optimization machinery (e.g., PyTorch/TensorFlow)

D.P. Kingma and J.L Ba, ICRL, 2015 (> 215k citations)

A. Paszke *et al.*, NEURIPS, 2019 (> 22k citations)

STL-10 dataset



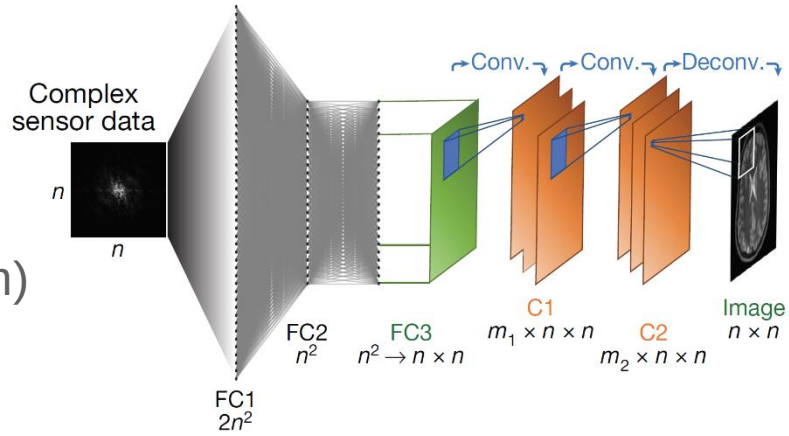
$$\{\boldsymbol{m}^{(\ell)}; \boldsymbol{f}^{(\ell)})\}_{1 \le \ell \le L}$$

Data-Driven Reconstruction Methods (2/3)

- **Reconstruction performance is empirically excellent but…**

… how to choose $\mathcal{G}_\theta$?

"Automap"
(> 6.10^9 param)



[B. Zhu et al., Nature Letters, 2018] (> 1.5k citations)

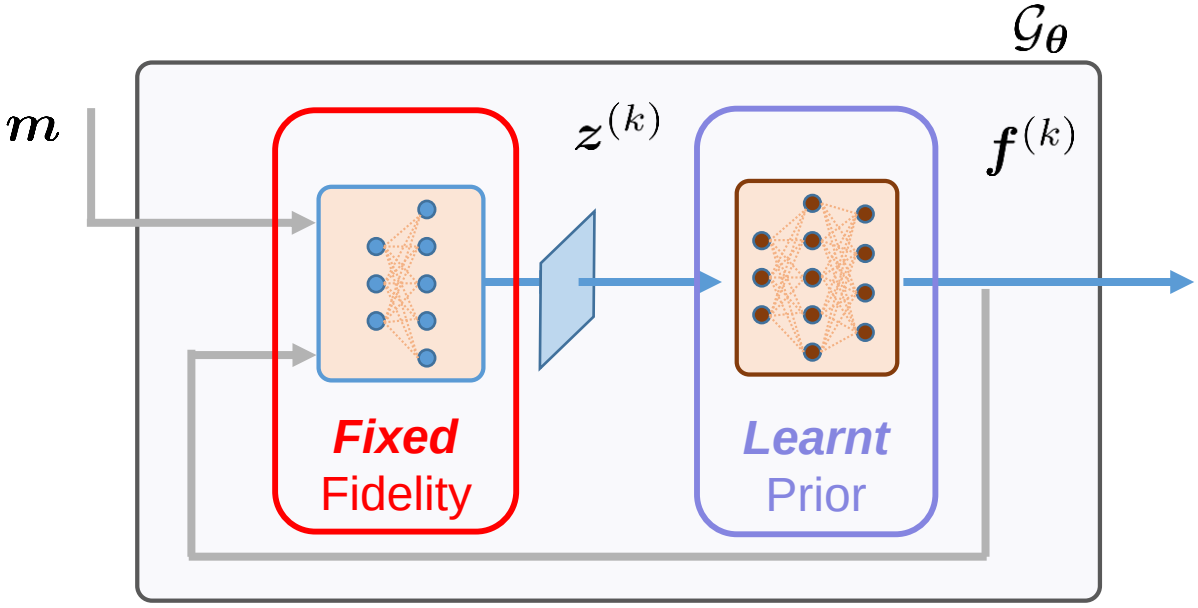
- Huge black-box? Interpretation? No mathematical or physical basis?

Data-Driven Reconstruction Methods (3/3)

- **Unrolled / Plug & Play methods**

Data fidelity: $\boldsymbol{z}^{(k)} = \boldsymbol{f}^{(k-1)} - \eta \boldsymbol{H}^\top (\boldsymbol{H}\boldsymbol{f}^{(k-1)} - \boldsymbol{m})$

Prior: $\boldsymbol{f}^{(k)} = \mathtt{prox}_{\eta\mathcal{R}}(\boldsymbol{z}^{(k)})$



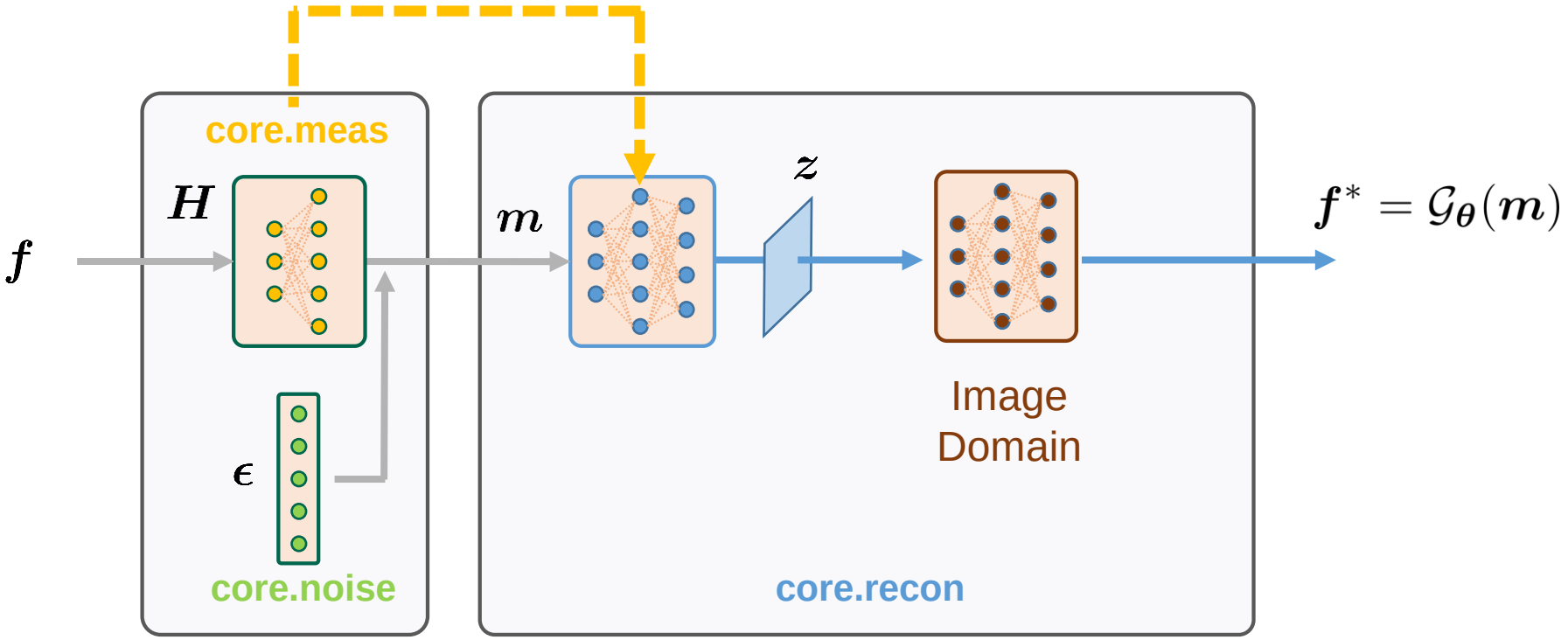
$\boldsymbol{f}^* = \boldsymbol{f}^{(K)} = \mathcal{G}_{\boldsymbol{\theta}}(\boldsymbol{m})$

network parameters

SPyRiT: Single-Pixel Reconstruction Toolkit

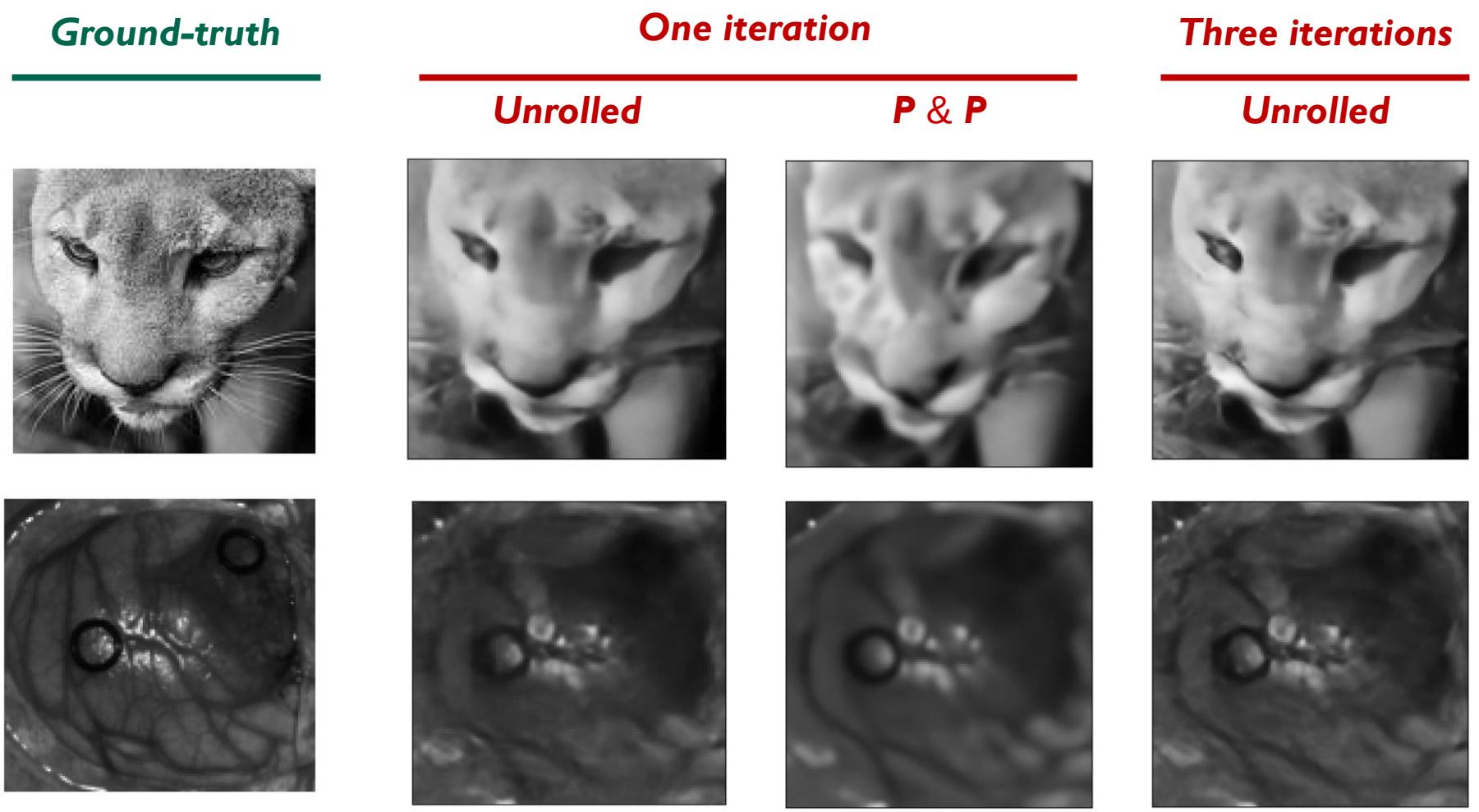
➢ Core components

spyrit



$$\theta^* \in \arg\min_{\theta} \frac{1}{L} \sum_{\ell} \|(\mathcal{G}_\theta \circ \mathcal{H})(f^\ell) - f^\ell\|_2^2$$

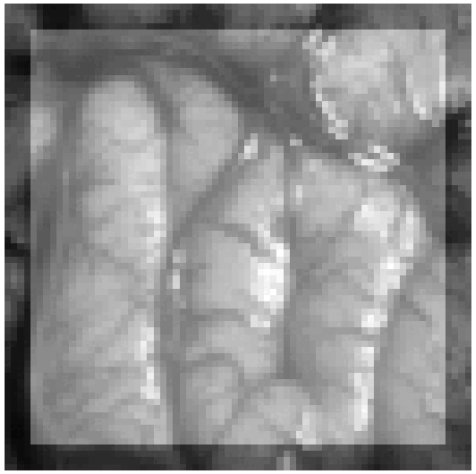
Coming Soon: New Unrolled and PnP Methods



Coming Soon: Dynamic Scenes

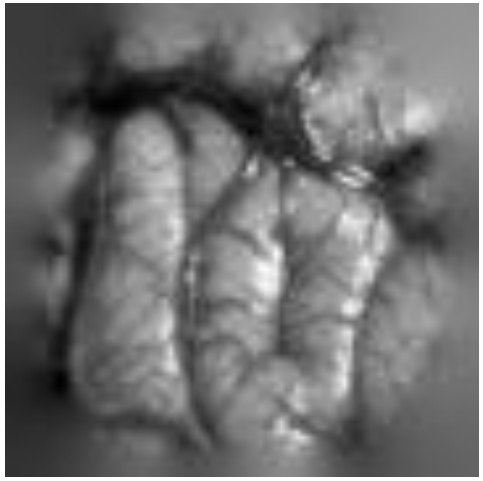
➢ Motion-compensated reconstruction

- ❖ Challenge of dynamic scenes: each pattern ‘sees’ a different image



$$m_k = \boldsymbol{h}_k^\top \boldsymbol{f}$$

No compensation



Compensated

[T. Maitre *et al*. *IEEE ISBI* (2024)]

Conclusions

https://github.com/openspyrit/

spyrit

- Existing unrolled and PnP methods
- Benchmark
- Tutorials

spas

- Open source Python package
- Instrumentation control (ViALUX DMD, Avantes spectrometer)

spihim

- 200+ hypercubes in open access
- Raw data, metadata

- Not limited to Hadamard, nor to the visible spectrum