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A fast computational approach for high spectral resolution imaging

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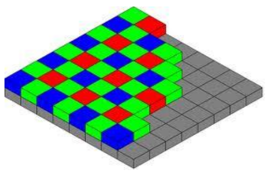
HYPERSPECTRAL IMAGING

Array

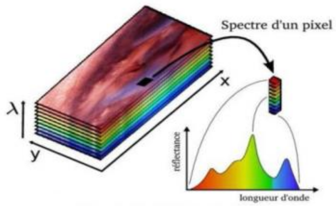
Point

Colour



Multi-spectral

Hyper-spectral

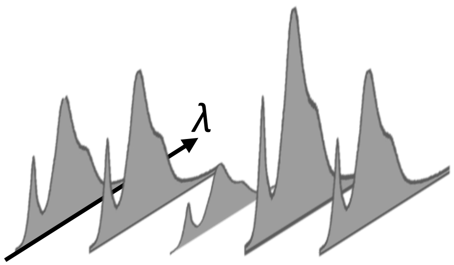


Spectrometer

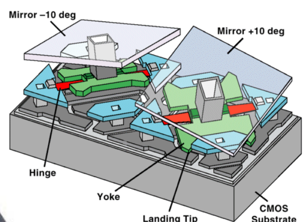
Spatial resolution			*Spatial resolution*
yes	yes	yes	no
Number of spectral channels			*Spectral channels*
3	2—10	10—1,000	100—2,000
Cost			*Cost*
~€1k	~€10k	~€20k-100k	~€1k

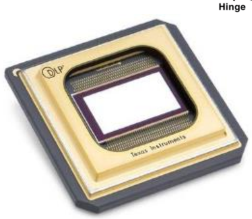
Need for **low cost array** with **high spectral** resolution

COMPUTATIONAL HYPERSPECTRAL CAMERA

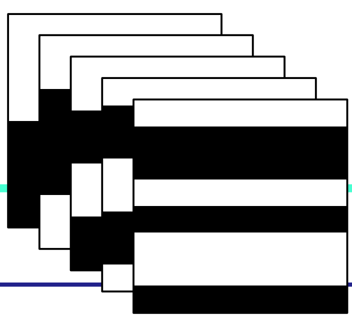


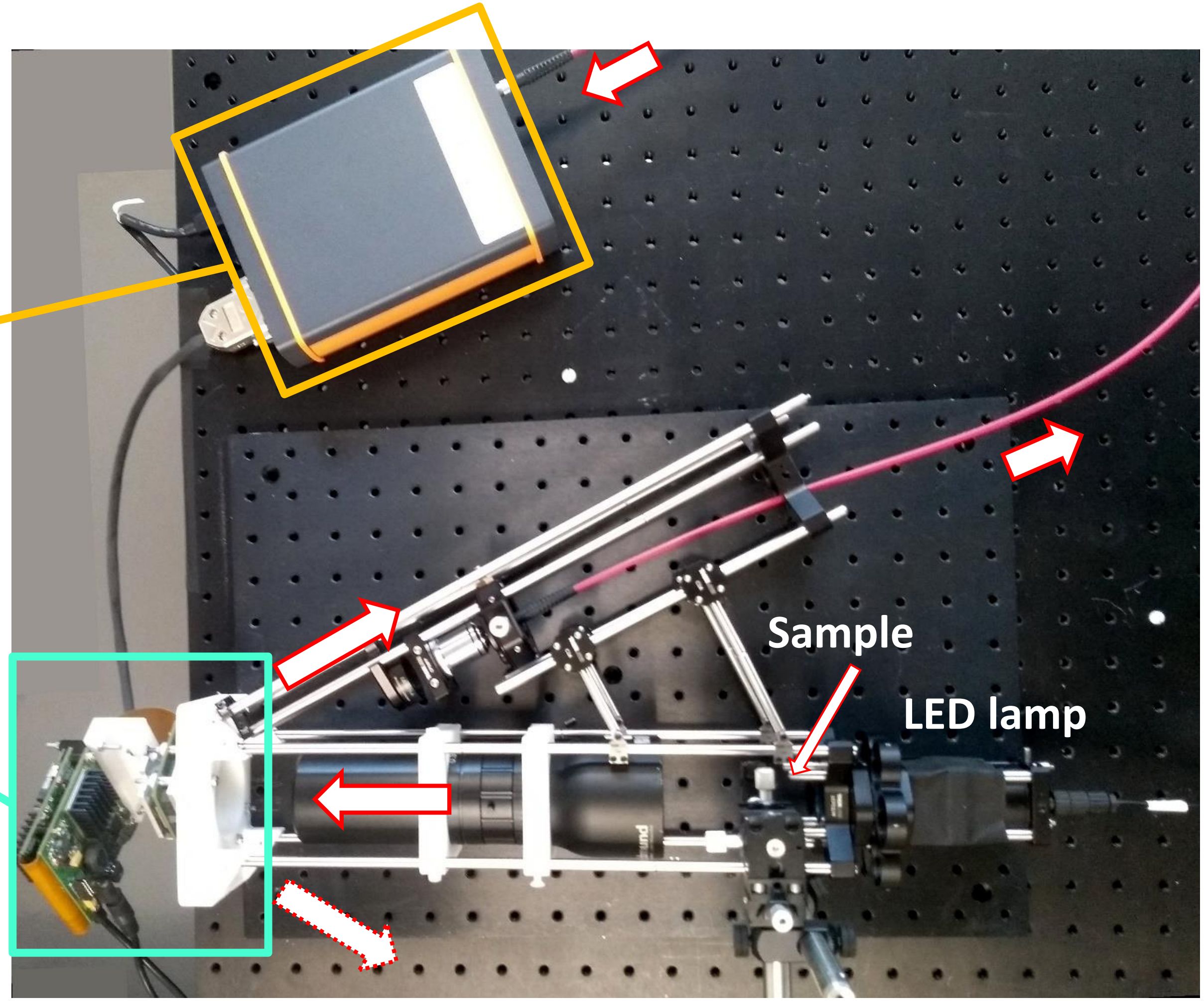
Spectrometer



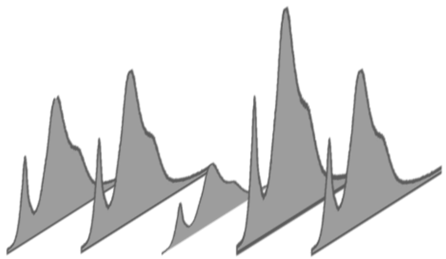


Spatial light modulator



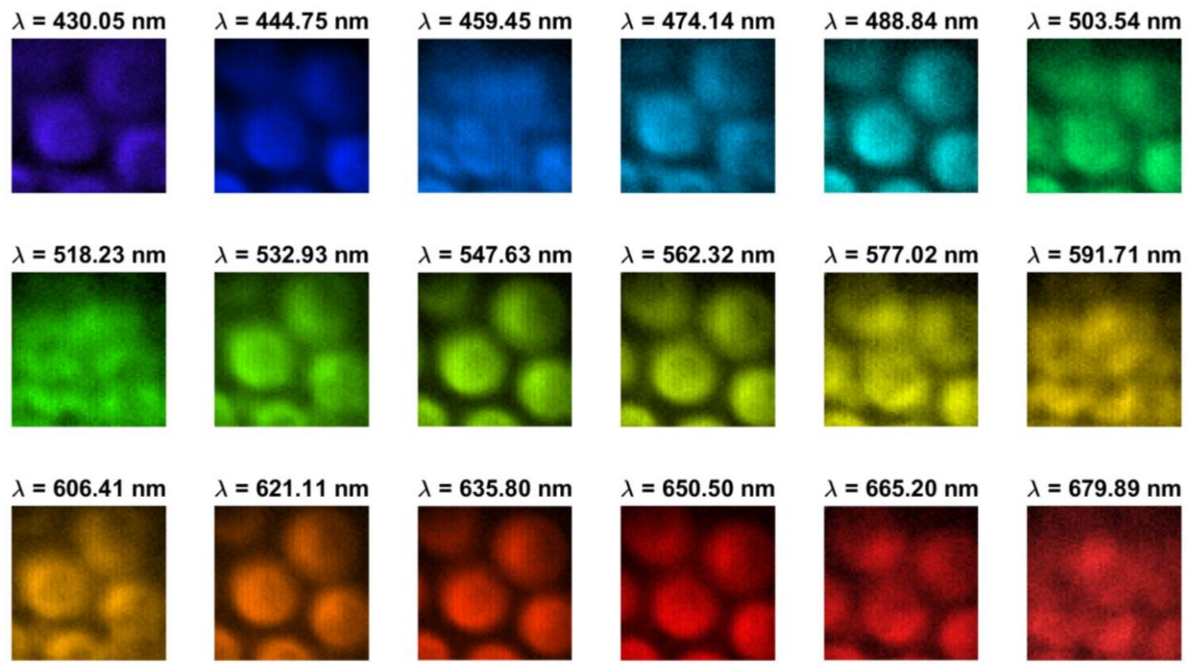


COMPUTATIONAL HYPERSPECTRAL CAMERA



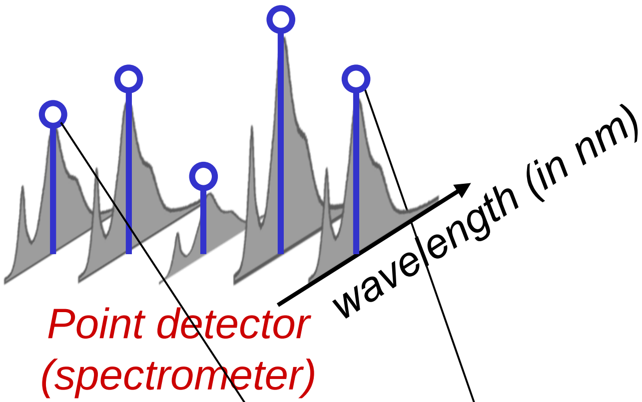
Spectrometer

Reconstruction



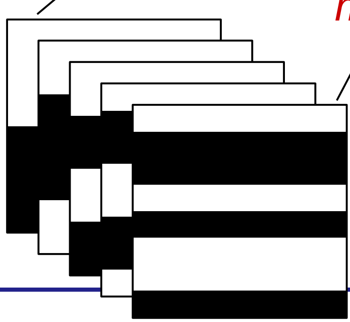
wavelength (in nm)

LED lamp



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

$$\boldsymbol{P} = [\boldsymbol{p}_1^\top, \dots, \boldsymbol{p}_M^\top]^\top \in \mathbb{R}^{M\times N}$$



- **Linear model**

$$\boxed{\boldsymbol{m}_\lambda = \boldsymbol{P}\boldsymbol{f}_\lambda}$$

1. “Weight design”: How to choose the patterns *P*?
2. Reconstruction: How to recover the image *f*?

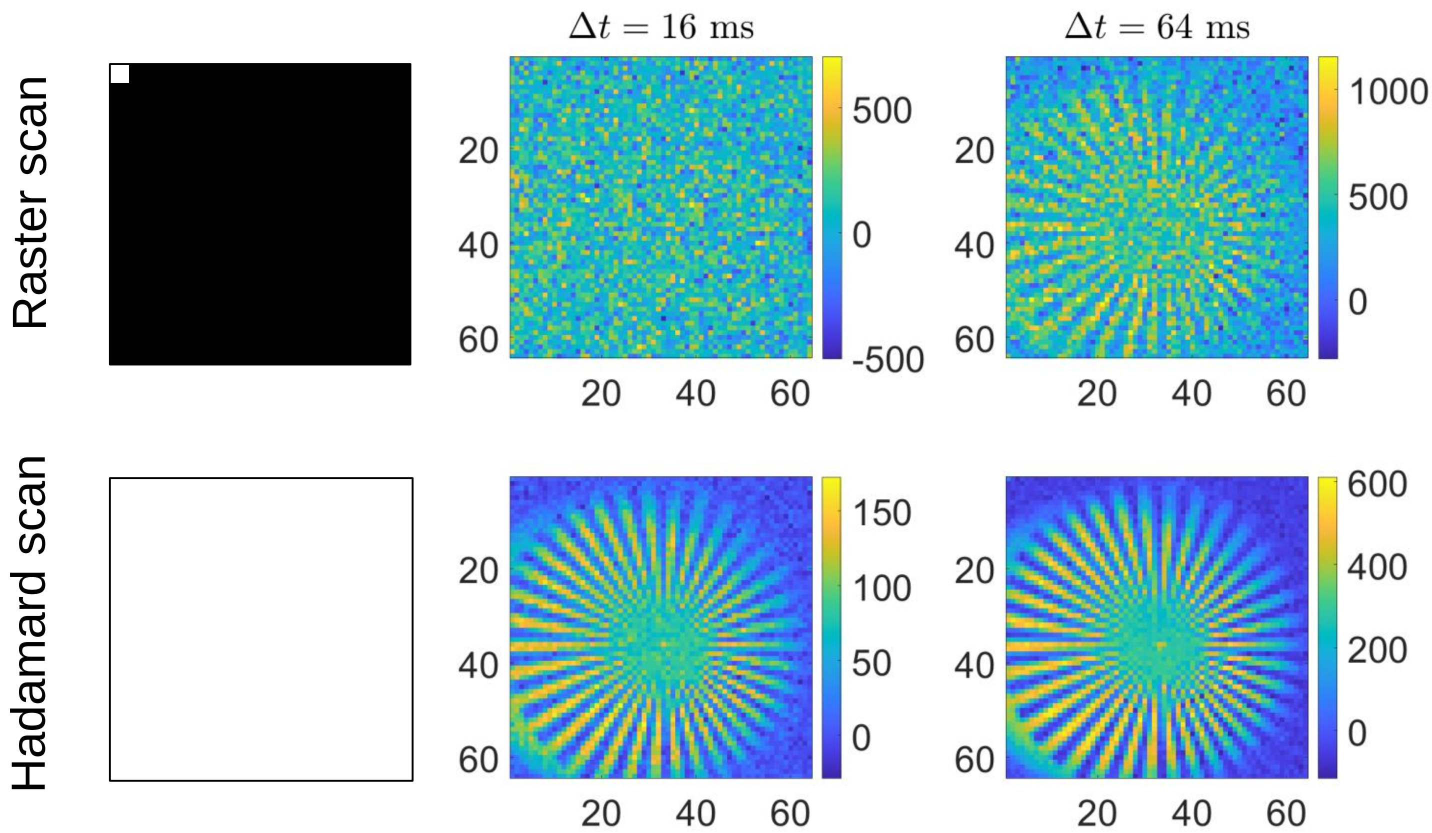
$M = N$

$$\boxed{\boldsymbol{f}_\lambda = \frac{1}{N}\boldsymbol{P}^\top \boldsymbol{m}_\lambda}$$

→ Hadamard patterns are optimal (for additive white Gaussian noise)

THE FELGETT SNR BOOST

➢ Hadamard optimality, a. k. a. Felgett's advantage



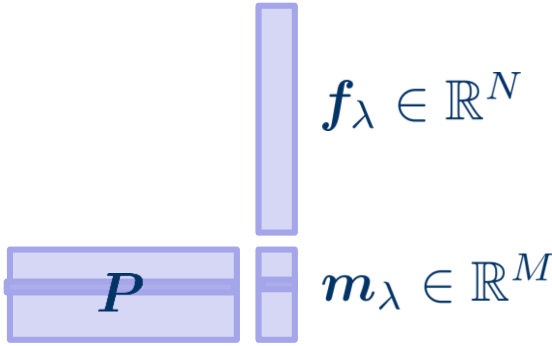
[N. Ducros *et al.*, working paper, 2022]

FAST ACQUISITIONS

- **Fast as subsampled acquisitions**
  - Sequential measurements lead to long acquisition times

  → Limit to a few patterns
  → This degrades the image resolution!

$M \ll N$



- How to recover the image ***f*** from ***m***?
  - Compressed sensing/constrained optimization

$$\min_{\boldsymbol{f}} \|\boldsymbol{m} - \boldsymbol{P}\boldsymbol{f}\|_2^2 + \alpha \mathcal{R}(\boldsymbol{f})$$

  - E.g., Total variation

$$\mathcal{R}(\boldsymbol{f}) = \|\nabla \boldsymbol{f}\|_1$$

… which requires iterative algorithms

256 × 256 image
M = 6,500 random measurements

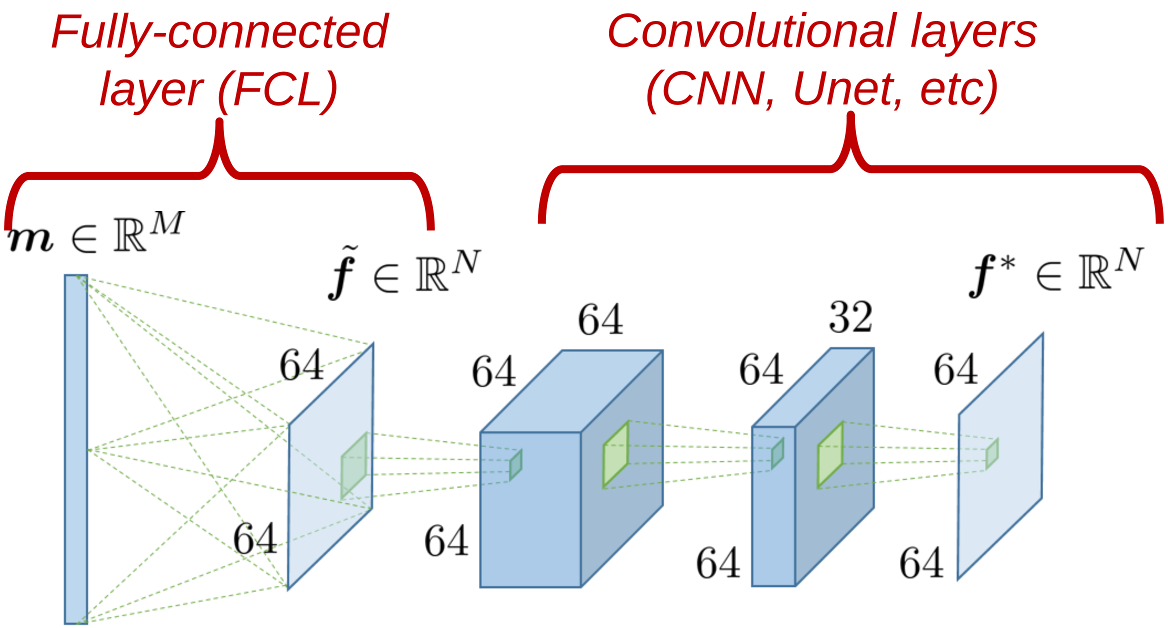
[Duarte *et. al*, IEEE SPM, 2008]

→ Fast acquisitions: long reconstructions!

DEEP RECONSTRUCTION (Free-Net)

- **Reconstruction:** How to recover the image $\boldsymbol{f}$ from $\boldsymbol{m}$?
  - Deep learning: Learn a nonlinear (reconstruction) mapping

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



[Higham *et al.*, Sci. Rep., 2018]

→ How to choose the non linear 'model' *H*?

→ How to interpret the output of this black box? Are there theoretical guarantees?

COMPLETION NETWORK (C-NET)

➢ Connection with Bayesian reconstruction

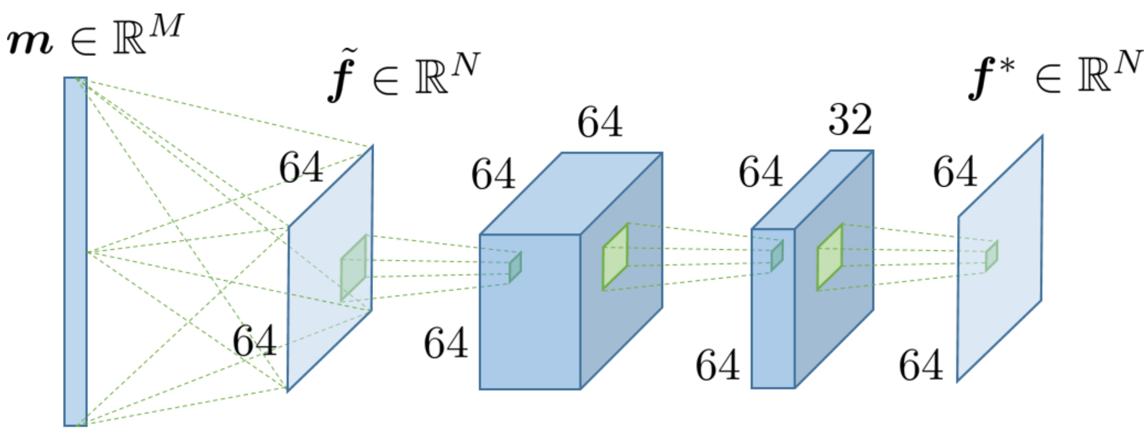
Completion approach

$$\boxed{\tilde{\boldsymbol{f}} = \frac{1}{N}\boldsymbol{P}^\top \begin{bmatrix} \boldsymbol{m} \\ \boldsymbol{y}_2 \end{bmatrix}}$$

$$\boldsymbol{y}_2(\boldsymbol{m}) = \boldsymbol{\mu}_2 + \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_1^{-1}(\boldsymbol{m} - \boldsymbol{\mu}_1)$$

Covariance between measured and missing

Covariance of measured



[N. Ducros *et al.*, IEEE ISBI 2020]

~1M param

~4k parameters

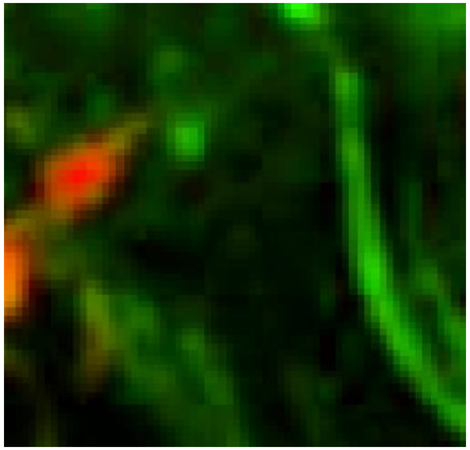
Fixed layer:
Gaussian completion

Learnable layer:
compensation for non-idealities

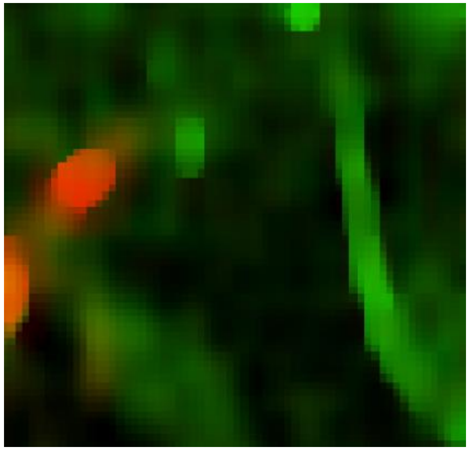
COMPLETION NETWORK (C-NET)

➢ **Fluorescence microscopy images (not in the STL-10 training set)**

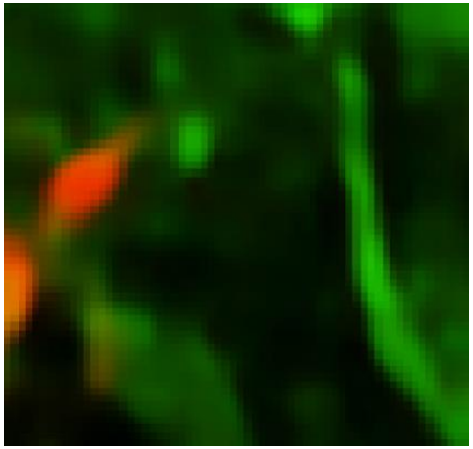
Ground-truth



Total Variation (TV)



C-Net



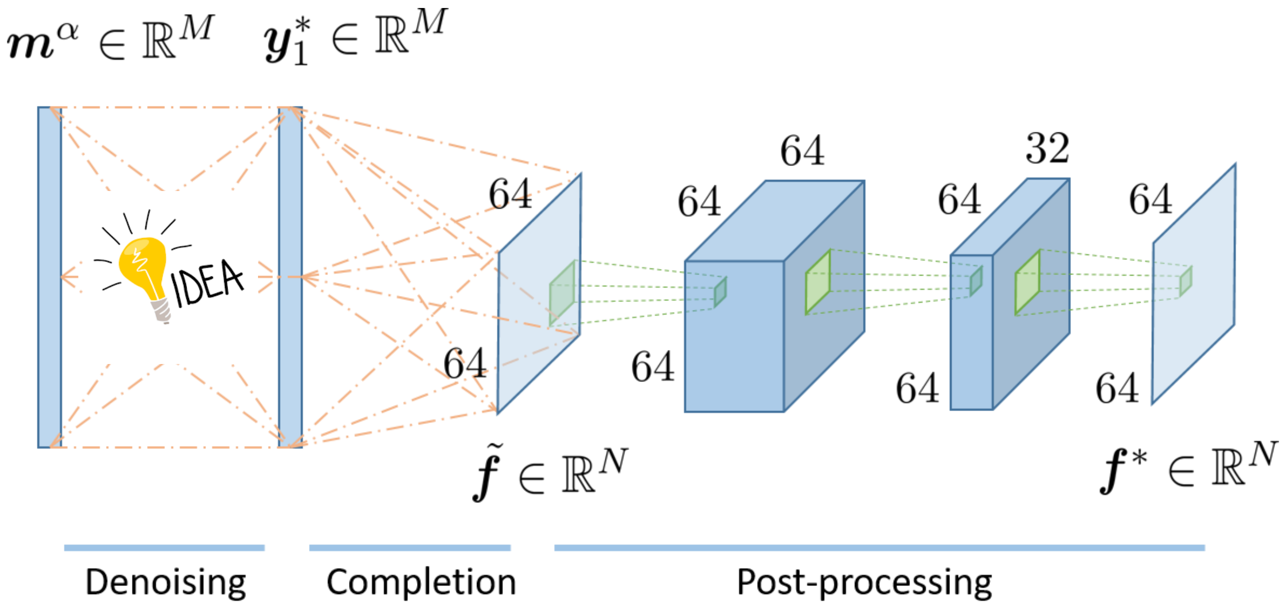
red: TV + **0.8** dB
green: TV + **1.16** dB

- Free-Net vs C-Net
  - Similar peak signal-to-noise ratios (<0.1 dB) performance
  - Free-Net has more parameters to train than C-Net (4M vs 4k)

- C-Net vs TV
  - C-Net has improved peak signal-to-noise ratios (~ +1 dB)
  - C-Net is faster than TV (typ. ~100 ms vs ~s)

DENOISED COMPLETION NETWORK (DC-Net)

- **Trained under Poisson noise with varying noise levels**



Fixed layer:
Gaussian ***denoised*** *completion*

Learnable layer:
compensation for non-idealities

[A. Lorente Mur *et al.*, Opt. Express (2021)]

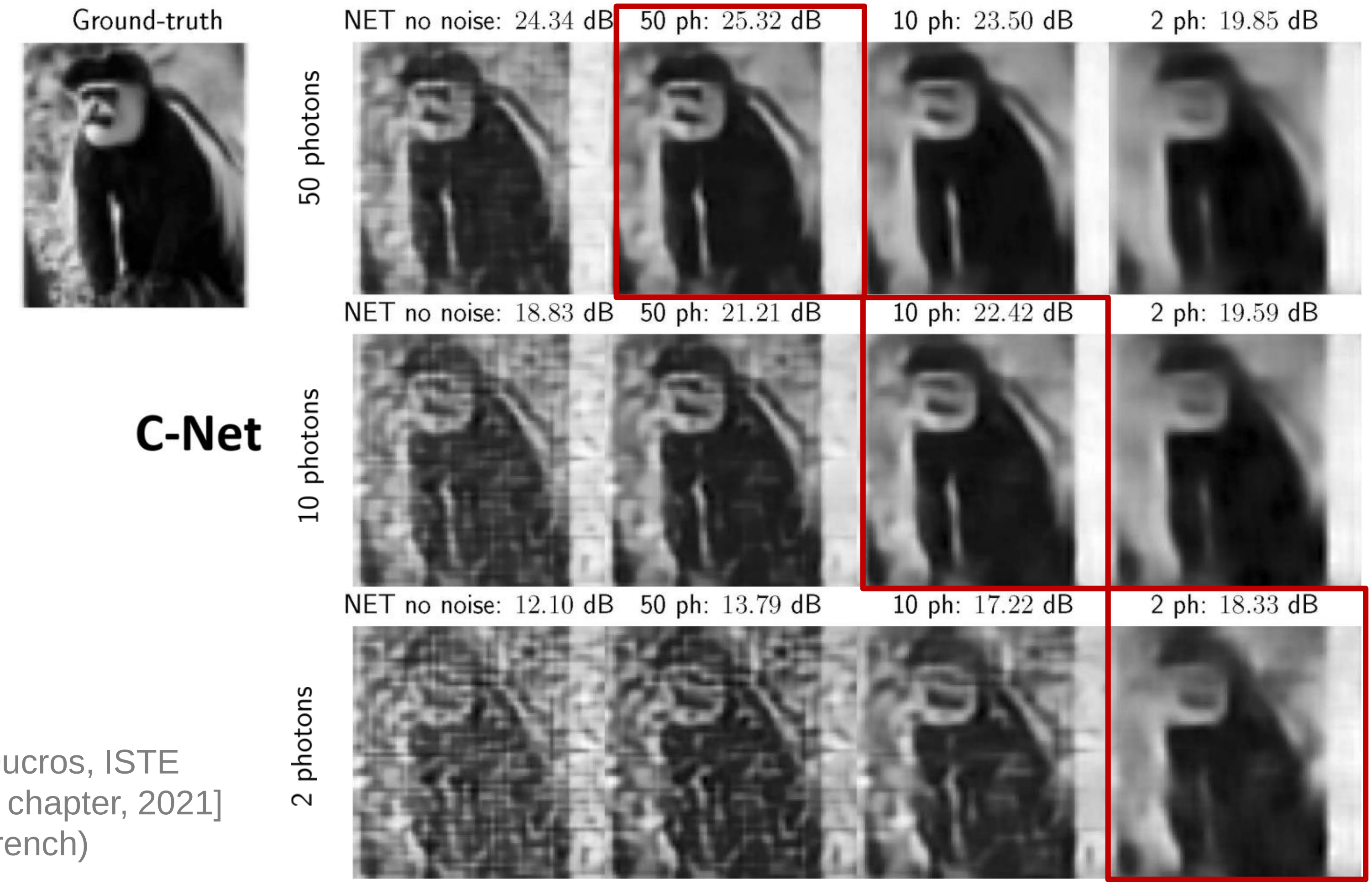
DENOISED COMPLETION NETWORK (DC-Net)

➢ **Noise robustness**

Increasing training noise

Ground-truth

C-Net



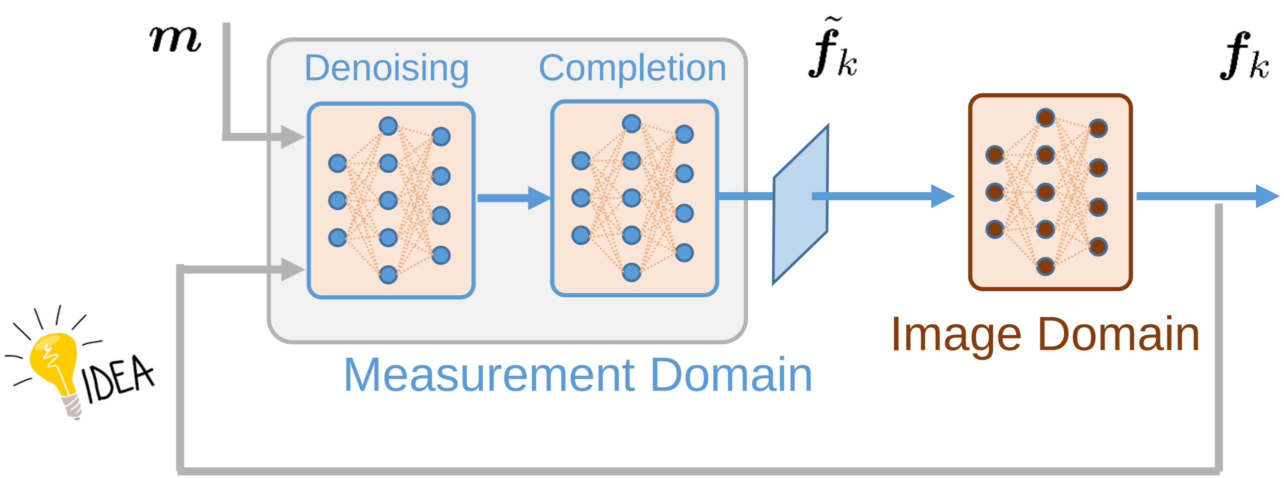
Increasing test noise

[N. Ducros, ISTE book chapter, 2021] (in French)

DEEP EXPECTATION MAXIMIZATION (EM-Net)

➢ Generalization

Denoising (measurements)	$\boldsymbol{y}_1^{(k)} = \boldsymbol{\sigma}_1^2/(\boldsymbol{\sigma}_1^2 + \tilde{\boldsymbol{\sigma}}_\alpha^2)(\boldsymbol{m}^\alpha - \boldsymbol{P}_1\boldsymbol{f}^{(k-1)})$
Completion (measurements)	$\boldsymbol{y}_2^{(k)} = \boldsymbol{\Sigma}_{21}\boldsymbol{\Sigma}_1^{-1}\boldsymbol{y}_1^{(k)}$
Update and mapping (image)	$\tilde{\boldsymbol{f}}^{(k)} = \boldsymbol{f}^{(k-1)} + \boldsymbol{P}^\top\boldsymbol{y}^{(k)}$
Denoising (image)	$\boldsymbol{f}^{(k)} = \mathcal{D}(\tilde{\boldsymbol{f}}^{(k)})$



[Lorente-Mur *et. al*, IEEE ISBI, 2021]

EXPERIMENTAL RESULTS

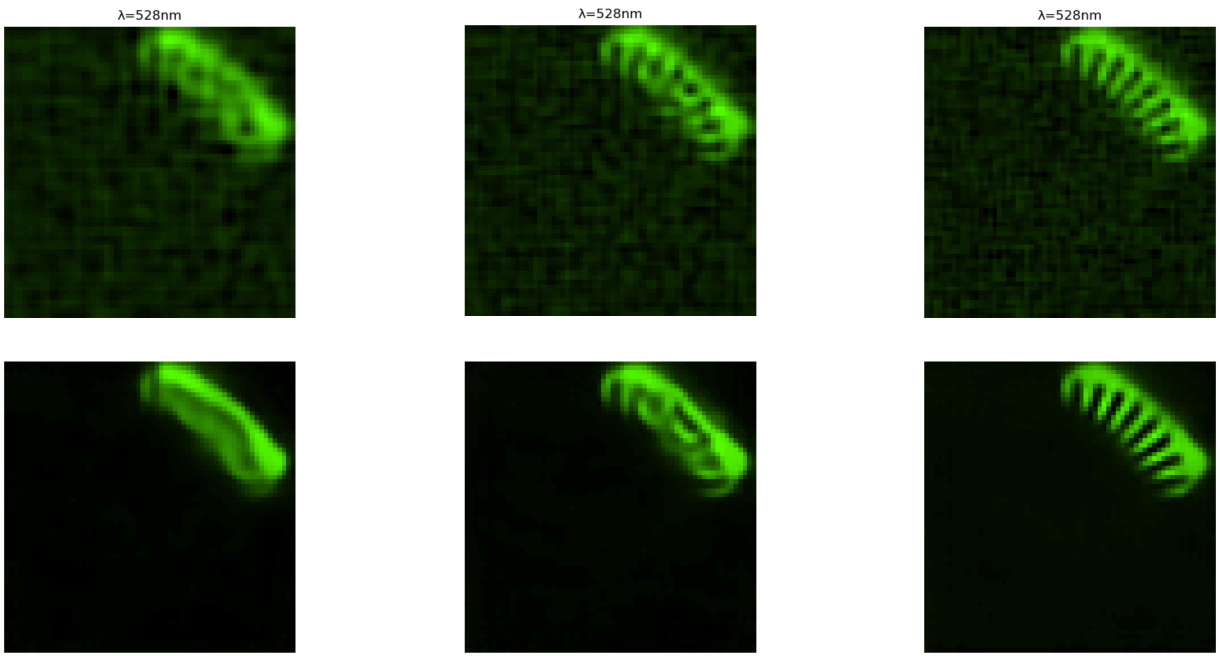
➢ Siemens resolution target + linear variable filter

+

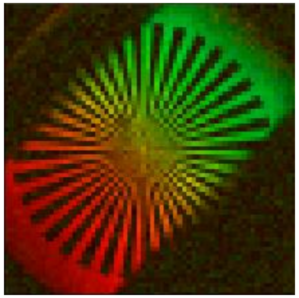
8x accel. (3 s) | 4x accel. (4 s) | 2x accel. (6 s)

Standard

EM-Net



Full (11 s)
RGB view



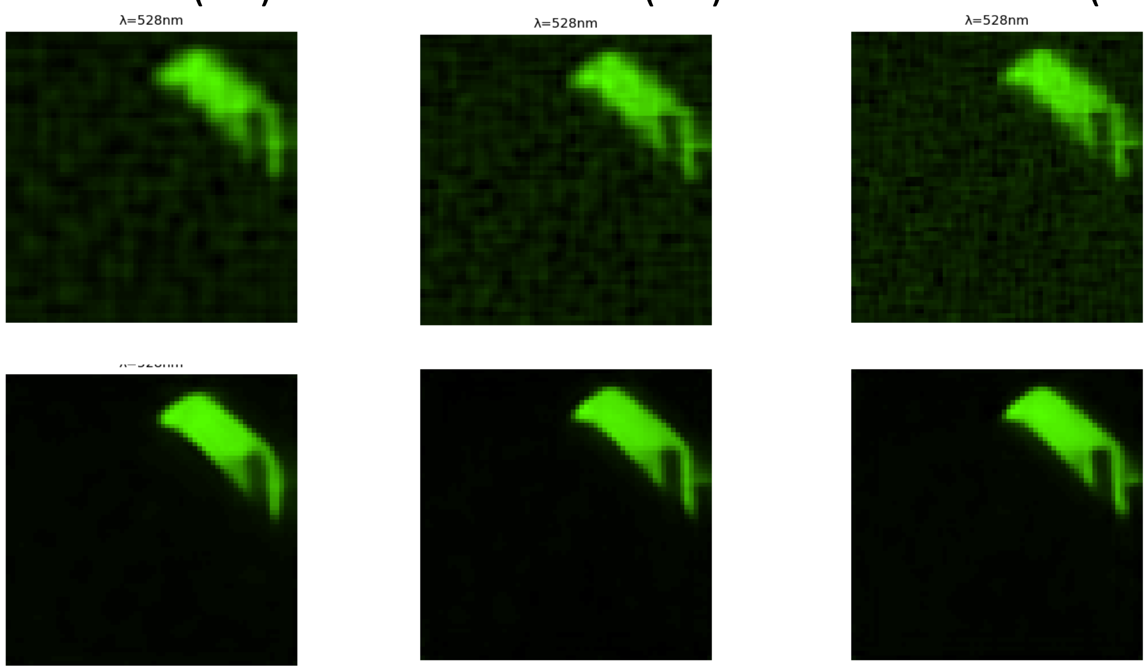
STL-10 cat + linear variable filter

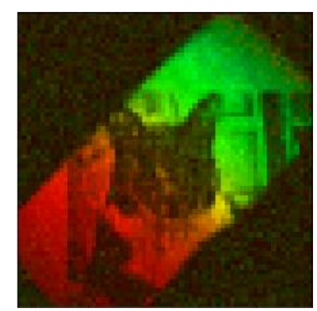
\+

8x accel. (3 s) | 4x accel. (4 s) | 2x accel. (6 s)

Standard

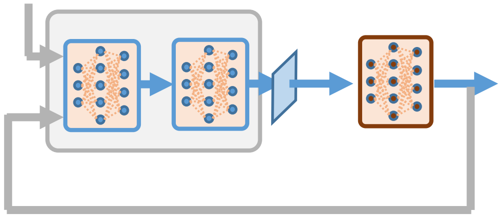
EM-Net

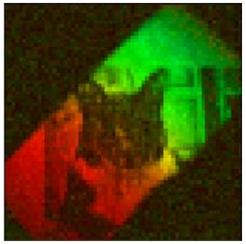




CONCLUSIONS

- **Computational imaging**
  - Computational hyperspectral imaging device
  - Deep reconstruction methods
    - DC-Net is robust to noise deviation
    - EM-Net requires fewer parameters





- **Open and reproducible research**
  - SPyRiT Python package: https://github.com/openspyrit
  - Datasets

- **Future work**
  - Image-guided neurosurgery (Protoporphyrin IX imaging)
  - Increase the spatial resolution/field-of-view
  - Increase the imaging speed

THANK YOU FOR YOUR ATTENTION