Hadamard spectral imaging

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Hyperspectral imaging

Challenge #1

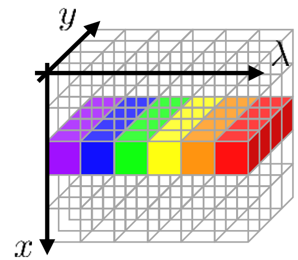
Resolution

Challenge #2

Speed

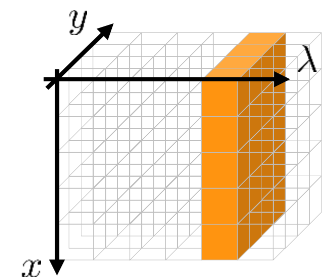
Challenge #3

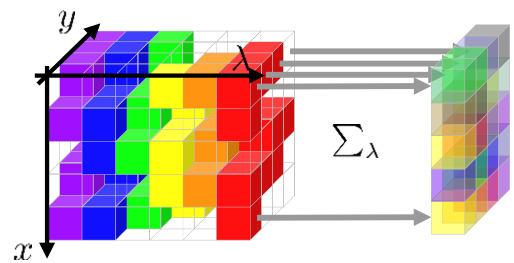
Weak signals



Pushbroom

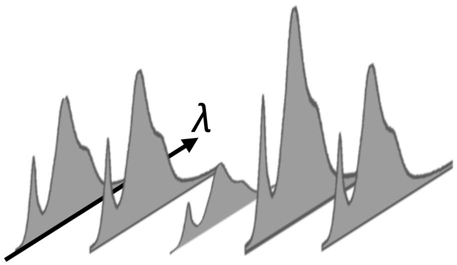
Optical filters



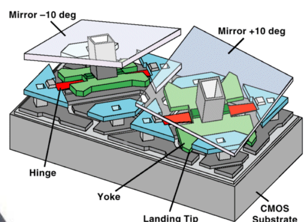


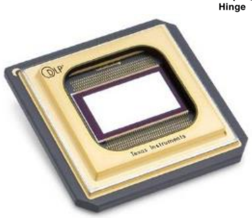
Computational

Hyperspectral single-pixel imaging

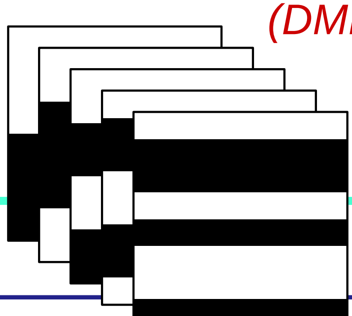


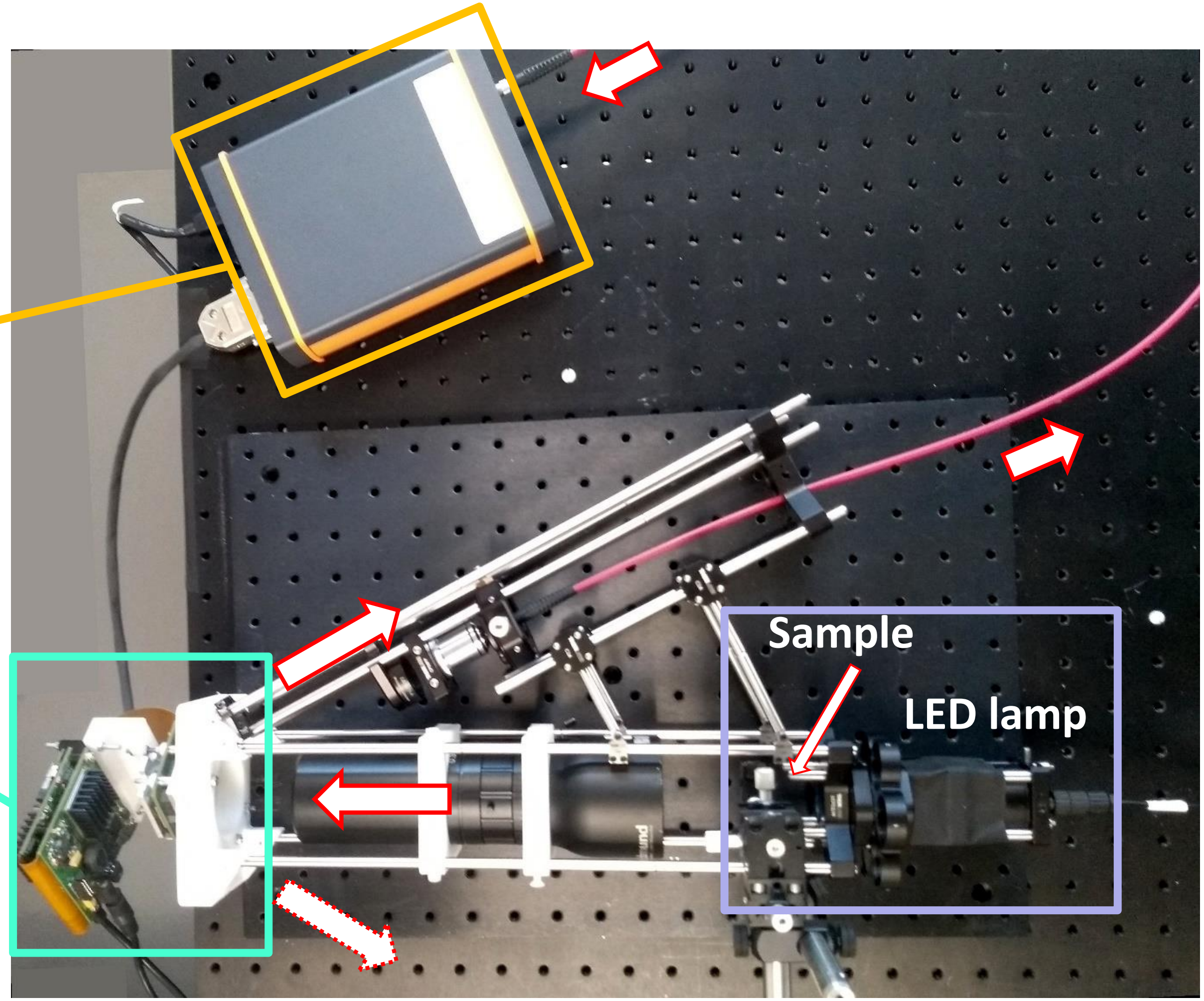
Spectrometer



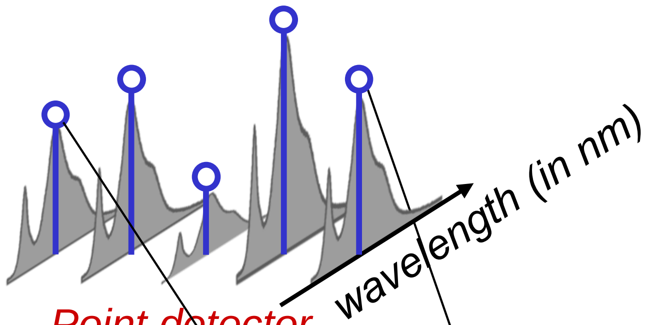


Digital Micromirror Device (DMD)



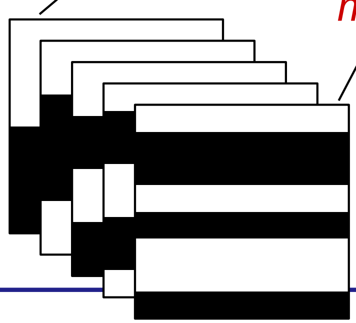


Hyperspectral single-pixel imaging



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

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



Acquisition

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

$$\boldsymbol{A} \in \mathbb{R}^{M \times N}$$

Reconstruction

$$\boxed{\boldsymbol{f}^* = \mathcal{R}(\boldsymbol{m})}$$

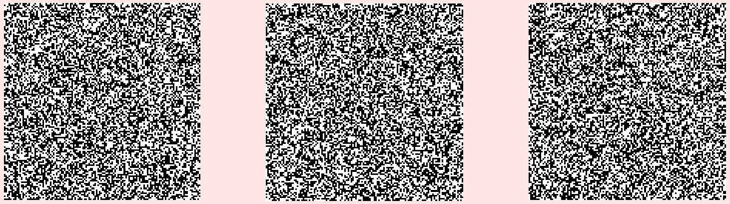
$$\mathcal{R}\colon \mathbb{R}^M \to \mathbb{R}^N$$

$$\boxed{(\boldsymbol{A}, \mathcal{R})\ ?}$$

Single-pixel imaging (2008)

> How to choose the acquisition–reconstruction pair $(\boldsymbol{A},\mathcal{R})$ if $M << N$?

Random (e.g., Bernouilli ½)



L1 minimisation

$$\min_{\boldsymbol{f}} \|\boldsymbol{m} - \boldsymbol{A}\boldsymbol{f}\|_2^2 + \lambda\|\boldsymbol{\Phi}\boldsymbol{f}\|_1$$

Original (256x256) | 1300 mes., x50 | 6500 mes, x10

[R. Duarte *et al.*, IEEE SPM 25, 2008] > 4k citations (Scholar)

Data-driven reconstruction (2018)

Neural network

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

Long training (~hours, days)

Fast inference (~milliseconds, seconds)

SCIENTIFIC REPORTS

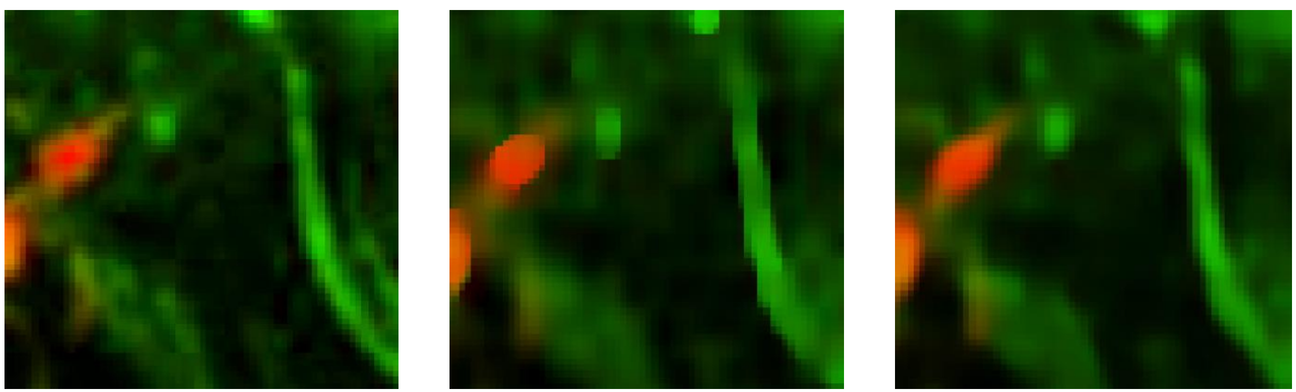
OPEN **Deep learning for real-time single-pixel video**

Catherine F. Higham[1], Roderick Murray-Smith[1], Miles J. Padgett[2] & Matthew P. Edgar[2]

[C. Higham *et al.*, Scient. Reports, 2018]

Fluorescence microscopy (malignant cells and vessels)

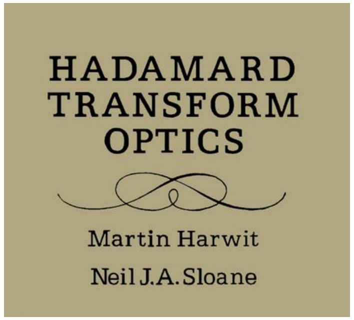
Ground-truth | Total variation | Neural network

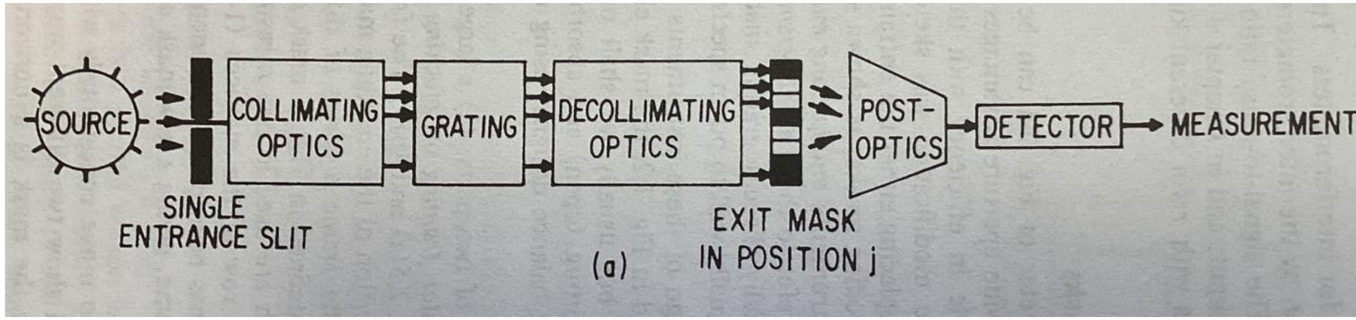


red: TV + **0.8** dB
green: TV + **1.16** dB

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

Hadamard spectroscopy (from the 70's)



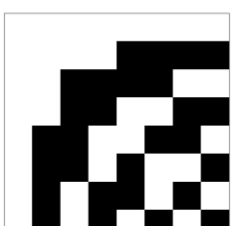


[M. Harwit and N Sloane, Academic Press, 1979]

'(…) conventional spectrometer is modified by using a <u>mask to encode the light</u> at the output'

Hadamard

$$\boldsymbol{A} \in \{-1, 1\}^{N \times N}$$



$$\boldsymbol{A}^\top \boldsymbol{A} = N \boldsymbol{I}_N$$

L2 minimization

$$\boldsymbol{f}^* = \frac{1}{N} \boldsymbol{A}\boldsymbol{m}$$

Fellgett's advantage

$$\text{Hyp}: \; m_i \sim \mathcal{G}(\mu = 0, \sigma^2)$$

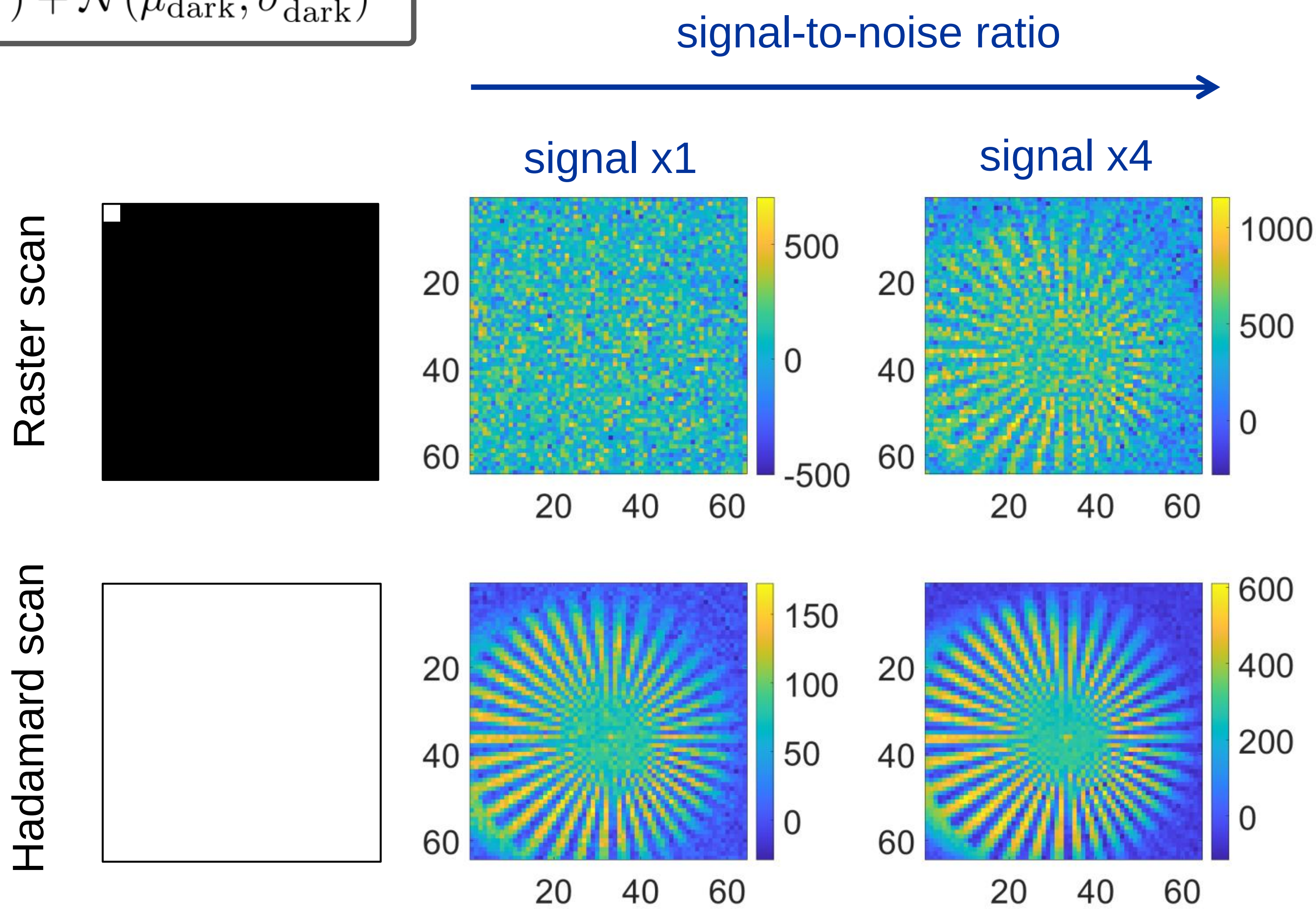
$$\mathrm{var}\left(f_n^*\right) = \frac{1}{N}\sigma^2 < \sigma^2$$

Improved SNRs

Fellgett's advantage

$$\boldsymbol{m} \sim g\mathcal{P}(\alpha \boldsymbol{A}\boldsymbol{f}) + \mathcal{N}(\mu_{\mathrm{dark}}, \sigma^2_{\mathrm{dark}})$$

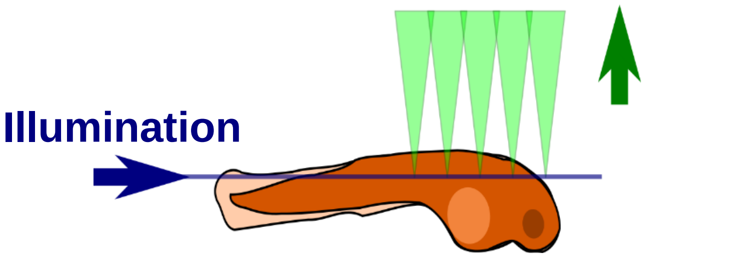
R1L1S2P



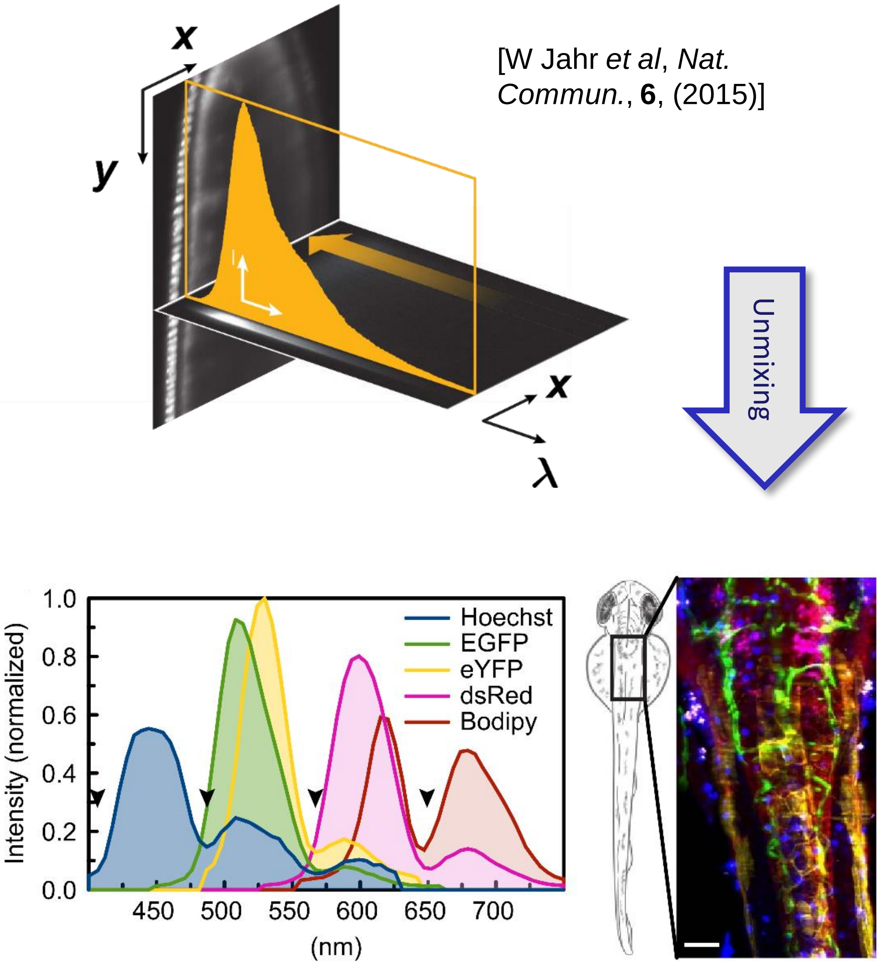
[N Ducros, unpublished results, 2020]

I - Fluorescence Microscopy

Fluorescence light sheet microscopy (FLSM)



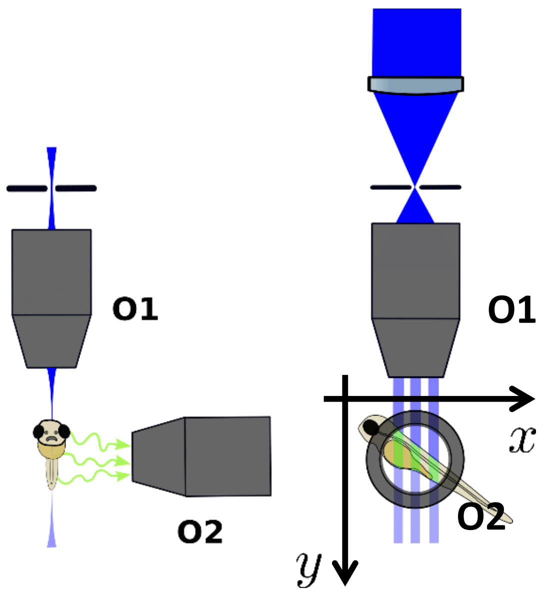
[Image adapted from Wikimedia Commons]

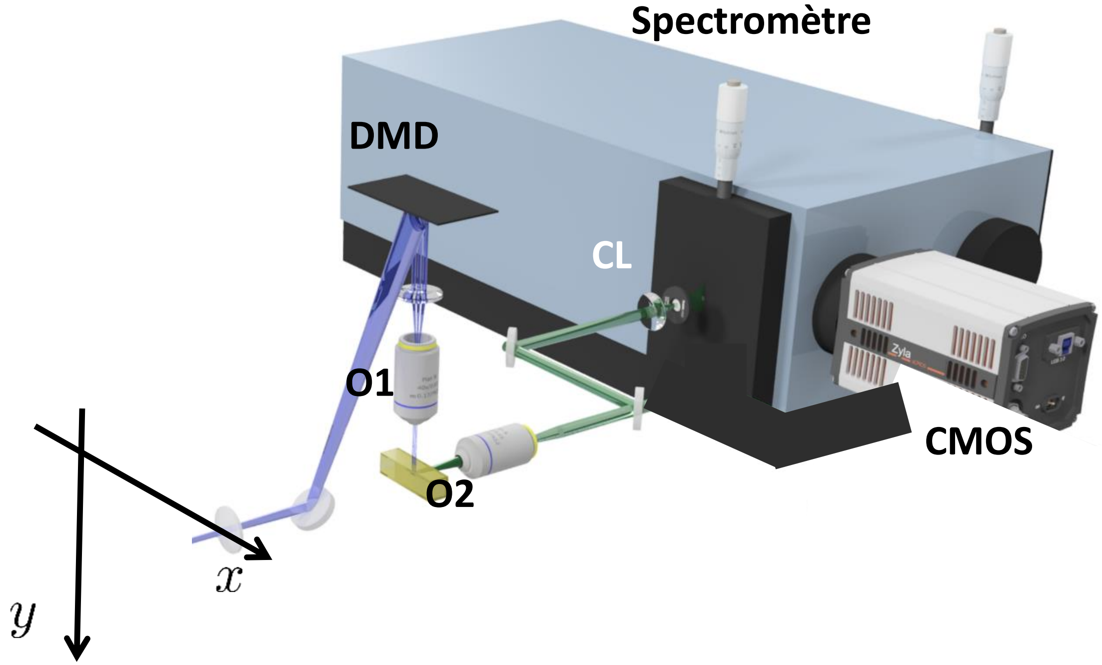


[W Jahr *et al*, *Nat. Commun.*, **6**, (2015)]

- ✓ Optical sectioning (6 µm resolution) as deep as 500 µm)
- ✓ Low photobleaching

Hyperspectral structured FLSM (HS-FLSM)

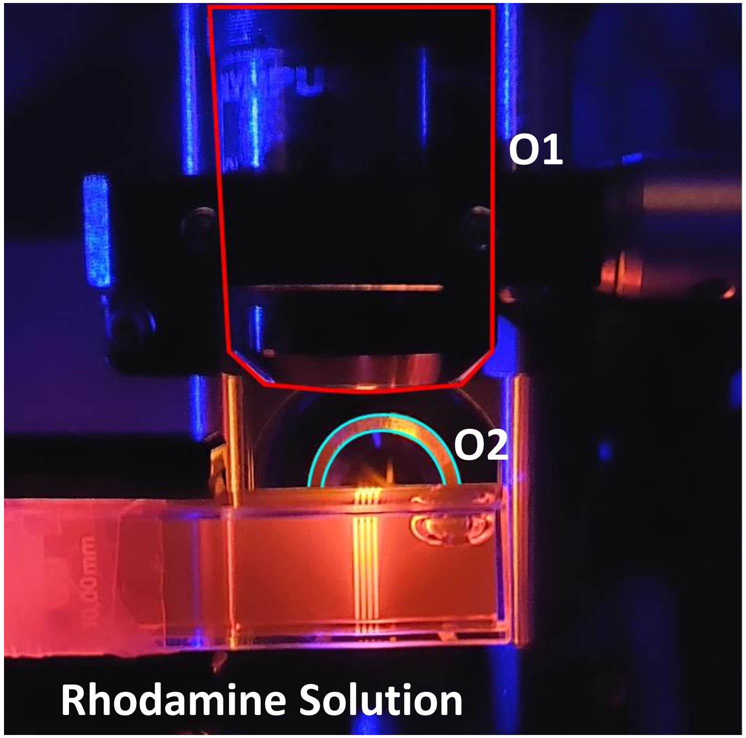




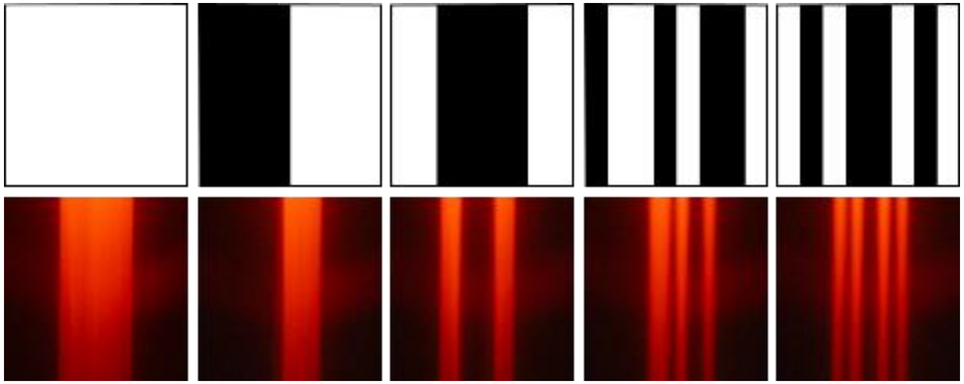
$$m_i(y, \lambda) = \int a_i(x) f(x, y, \lambda)\, \mathrm{d}x, \quad 1 \leq i \leq M$$

[S. Crombez *et al*. Opt. Express **30**, 2022]

Structured light sheets



DMD (top) vs experimental (bottom) light patterns

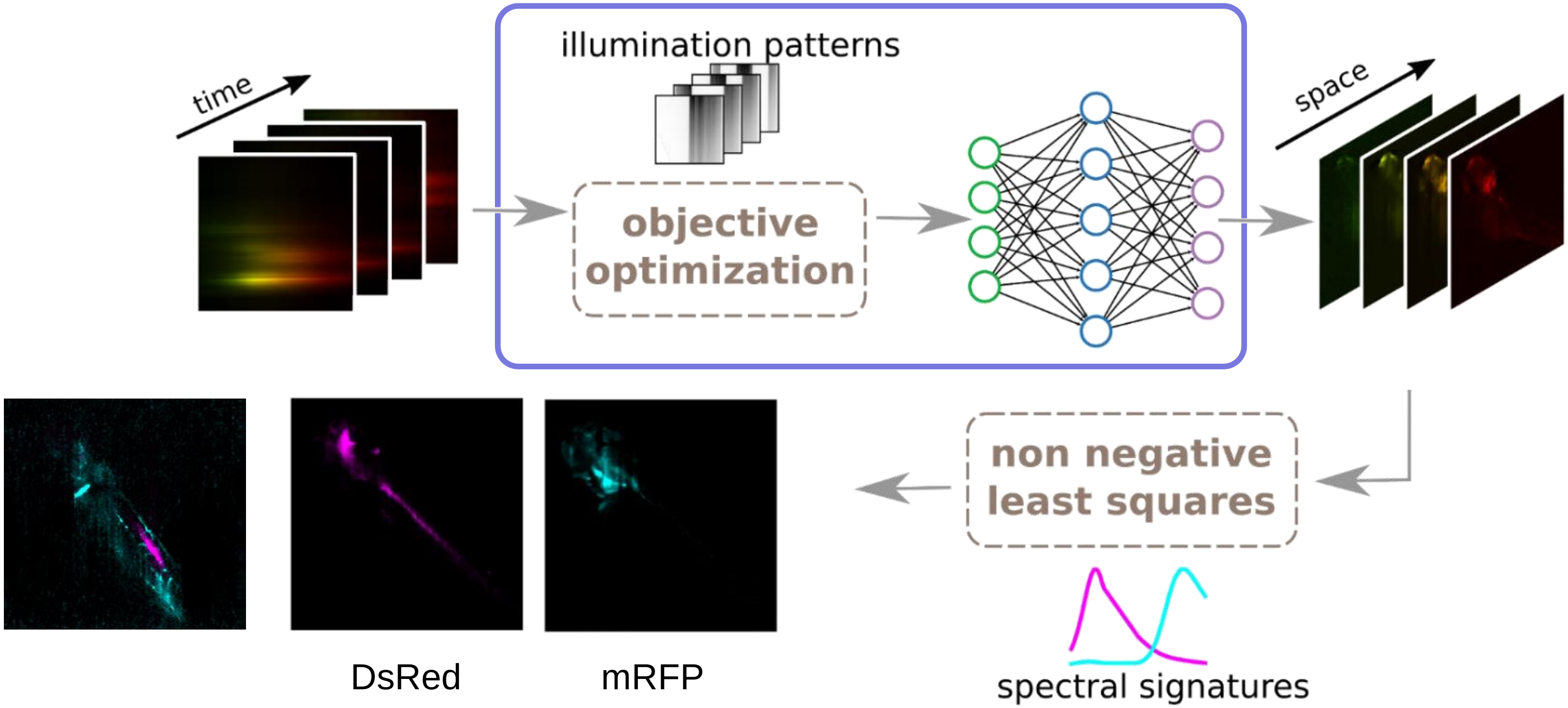


- ✓ Light patterns need to be calibrated
- ✓ “Good” patterns (e.g., system matrix with low condition number) are highly desirable

[S. Crombez *et al*. Opt. Express **30**, 2022]

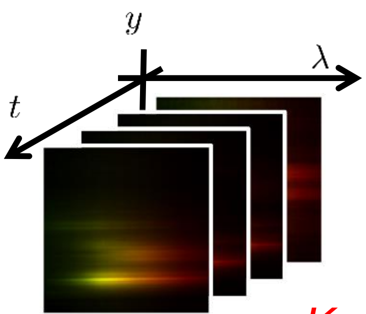
High-resolution quantitative HS-FLSM

Proof of principle

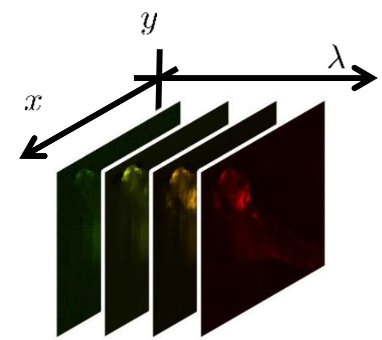


[S. Crombez *et al.*, unpublished, 2024]

HS-FLSM data-driven reconstruction



$$M_\lambda = A F_\lambda + E, \quad 1 \le \lambda \le \Lambda,$$



K x *N*$_y$
measurements

K x *N*$_x$
system matrix

N$_x$ x *N*$_y$
hypercube slice

Slice-by-slice reconstruction

$$F^*_\lambda = \mathcal{R}_{\theta^*}(M_\lambda) \text{ for all } \lambda$$

Fast inference/small network
Training from grayscale image

End-to-end training / MMSE

$$\theta^* \in \arg\min_{\theta} \frac{1}{L} \sum_{\ell} \|\mathcal{R}_{\theta}(M^\ell) - F^\ell\|^2_{\mathrm{F}}$$

No *regularization/prior* along the spectral axis

HS-FLSM data-driven reconstruction

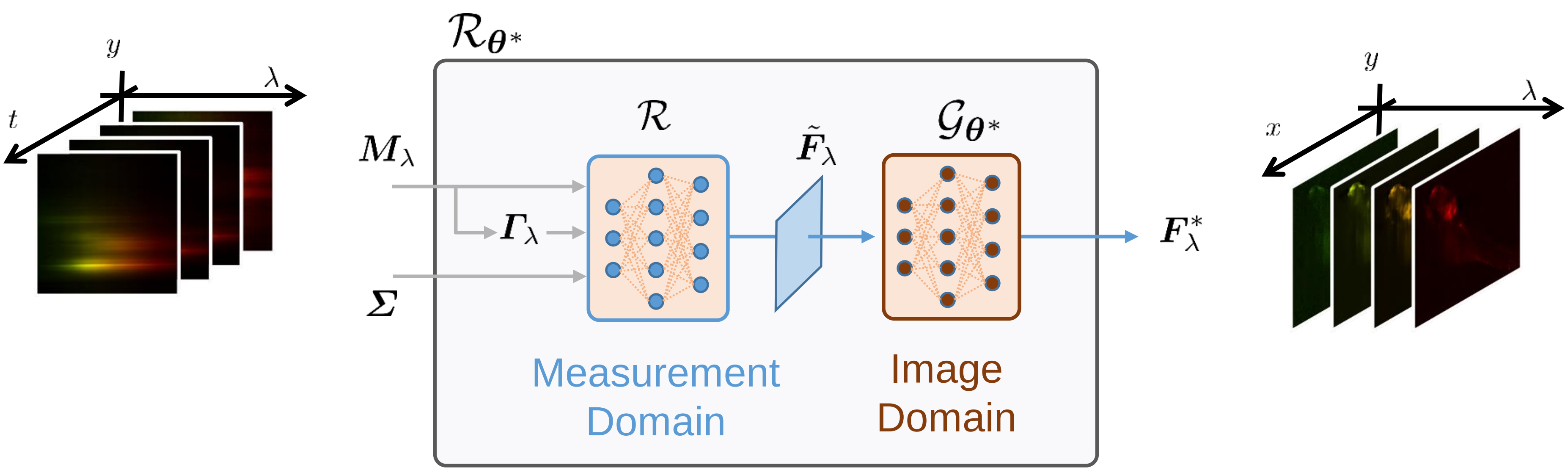
Challenges
- ✓ Handle varying noise levels
- ✓ Avoid spectral distortions

image profile covariance

measurement covariance

Tikhonov (*x*-axis only) : $$\mathcal{R}(\boldsymbol{M}_\lambda) = \boldsymbol{\Sigma}\boldsymbol{A}^\top\left(\boldsymbol{A}\boldsymbol{\Sigma}\boldsymbol{A}^\top + \boldsymbol{\Gamma}_\lambda\right)^{-1}\boldsymbol{M}_\lambda$$

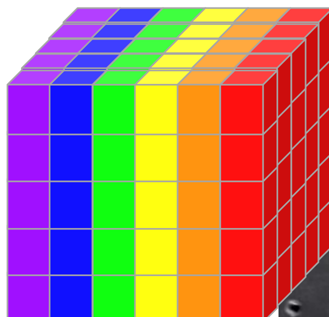
Data-driven (*x*- and *y*-axis) : $$\mathcal{R}_{\boldsymbol{\theta}^*}(\boldsymbol{M}_\lambda) = (\mathcal{G}_{\boldsymbol{\theta}^*} \circ \mathcal{R})(\boldsymbol{M}_\lambda)$$

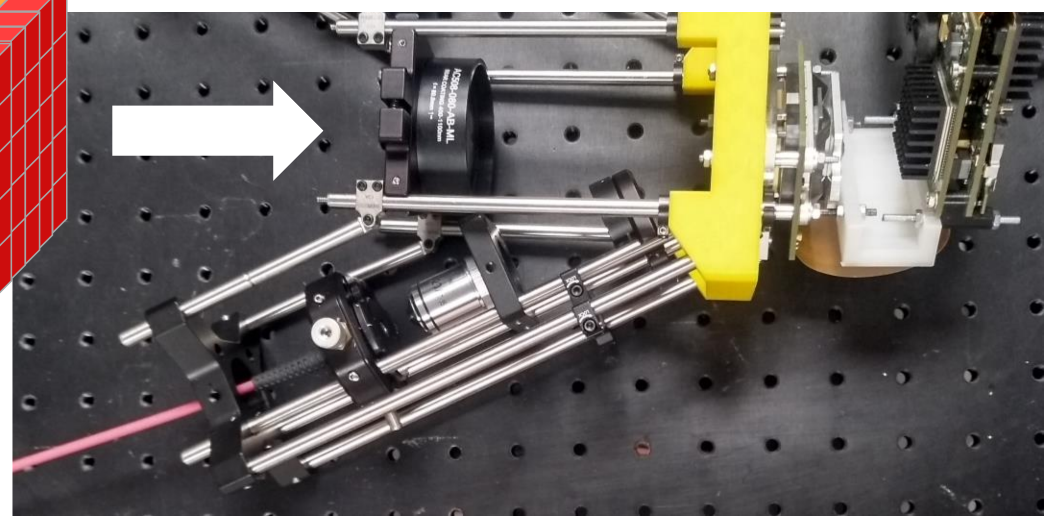


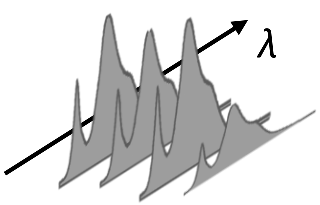
II – Two-arm (passive) imaging

Two-arm hyperspectral imaging

Spatial resolution ++
Temporal resolution ++





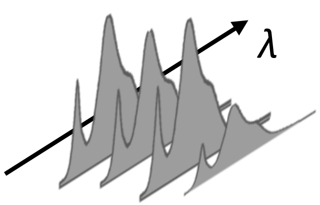


300+ hypercubes in open access
https://github.com/openspyrit/spihim

64 × 64 × 2048 cube in 10 s

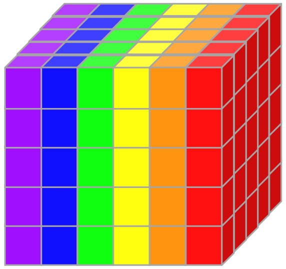
Two-arm hyperspectral imaging

Spatial resolution ++
Temporal resolution ++



Spectral resolution ++

1. Spatial **and** spectral resolution ++

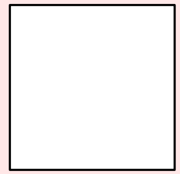


2. Temporal resolution ++

3. Design the patterns (E.g., optimisation of the time budget / SNR / acquisition speed, etc.)

Dynamic imaging: motion compensation

Dynamic forward problem

$$m_k = \langle a_k, f_k \rangle = $$ ⟨  ,  ⟩

$$f_k(\boldsymbol{x}) = f(\boldsymbol{x}, t_k)$$

Motion compensation

Deformation

Reference (motion-compensated) image

$$(f_k \circ v_k)(\boldsymbol{x}) = f_{\mathrm{ref}}(\boldsymbol{x})$$

$$v_k : \mathbb{R}^2 \to \mathbb{R}^2$$

Hyp : v_k can be estimated from the imaging arm

$$m_k = \langle h[v_k], f_{\mathrm{ref}} \rangle$$

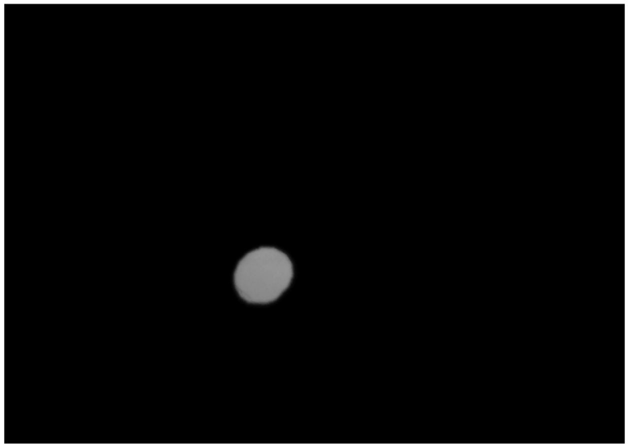
[T. Maitre *et al*., IEEE ISBI, 2024]
[T. Maitre *et al*., MICCAI, 2024]

Reconstruction

$$\boldsymbol{f}^*_{\mathrm{ref}} \in \arg\min_{\boldsymbol{f}} \|\boldsymbol{m} - \boldsymbol{H}\boldsymbol{f}\|_2^2 + \mathcal{J}(\boldsymbol{f})$$

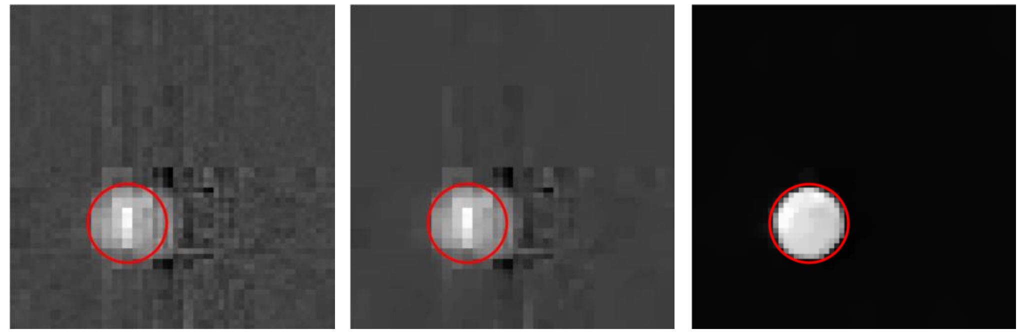
Dynamic imaging: motion compensation

Grayscale (experimental)



Hyperspectral

Static — *Static TV* — *Dynamic TV*



[T. Maitre *et al.*, IEEE ISBI, 2024]

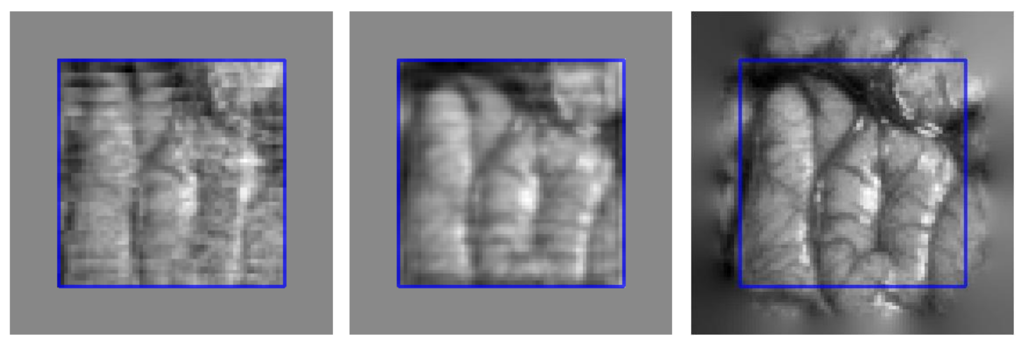
$$\mathcal{J} = \|\nabla \cdot\|_1$$

Grayscale (simulated)

DMD area = reference frame FOV

Hyperspectral

Static — *Dynamic* H^1 — *Extended* H^1



[T. Maitre *et al.*, MICCAI, 2024]

$$\mathcal{J} = \frac{1}{2}\|\nabla \cdot\|_2^2$$

Limitations and future work

Limitations

LSFM
- Spatial resolution ~7 x 2 µm^2
- Acquisition speed ~8 min/slice

Passive imaging
- Extended FOV using experimental measurements
- Typical acquisition time is ~10 s

Future work (hardware)

LSFM
→ Improved beam shaping along *x*-axis (~500 x 500 nm^2 ?)
→ Z-axis beam shaping

Passive imaging
→ *x*-axis only modulation

Future work (software)

→ Reconstruct and unmix jointly [S. Hariga *et al.*, EUSIPCO, 2024]
→ Data-driven (e.g., unrolled, PnP) for 3D spectral reconstruction
→ 2-arm acquisition/data fusion
→ Design of the patterns
→ Etc.

https://spyrit.readthedocs.io/
https://pilot-warehouse.creatis.insa-lyon.fr/