

Habilitation à diriger des recherches
Soutenue publiquement le vendredi 28 juin 2024

Algorithmes pour l'imagerie optique computationnelle par rayons X et dans le visible

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2004 — 2006

2007 — 2009

2010 — 2012

2013

2013 — 2024

ECOLE D'INGENIEURS
**TELECOM
PHYSIQUE
STRASBOURG**



POLITECNICO
MILANO 1863



INSA INSTITUT NATIONAL
DES SCIENCES
APPLIQUÉES
LYON



**Ecole
Ingénieur
+ Master**

Doctorat

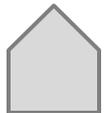
**Post-
doctorat**

**Ingénieur
recherche**

**Maître de
conférences**

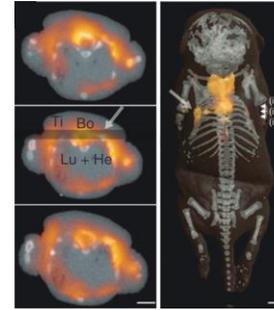
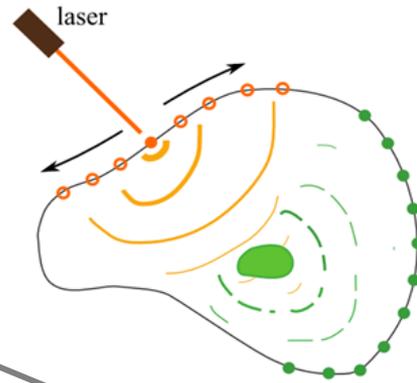


**Prix de thèse
en bio-ingénierie**



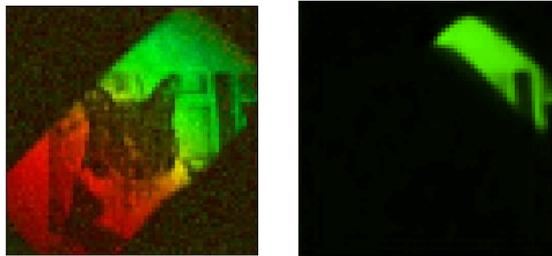
IUF institut
universitaire
de France

1 – Tomographie optique diffuse



[A. Ale *et al.* Nat. Methods **9**, 615 (2012)]

- Lumière visible/proche IR
- Milieu « turbide »
- Absorption/diffusion
- Concentration/temps de vie des fluorophores



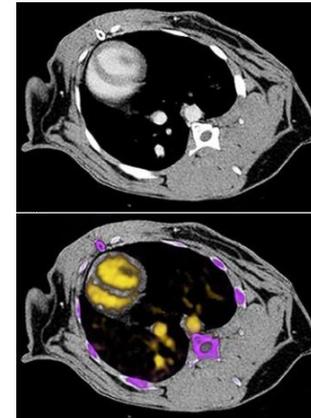
[G. Beneti Martins *et al.* Opt. Express **31**, 15599 (2023)]

- Images 2D, 3D
- Lumière visible

Mais aussi :

- IR, THz, X, neutrons

2 – Tomodensitométrie (TDM) spectrale



[D.P. Cormode *et al.* Sci. Rep. **7**, 4784 (2017)]

- Rayons X
- Densité des constituants/matériaux
- Agent de contraste (*k-edge*)

3 – Imagerie optique computationnelle

5 thèses soutenues

2 thèses en cours

10 Masters

4 Postdoc/Ingé

2015

2017

2019

2021

2023

2025

F Rousset



*Cotutelle Polimi
Prix de thèse des «
Amis de l'Université
de Lyon »*



A Lorente Mur



S Hariga

**Opt.
Comput.**

**TDM
spectrale**



S Bussod



T Hohweiller



V Pronina



T Maitre



JFPJ Abascal
Marie Curie Fellow

P. Leclerc

S Crombez

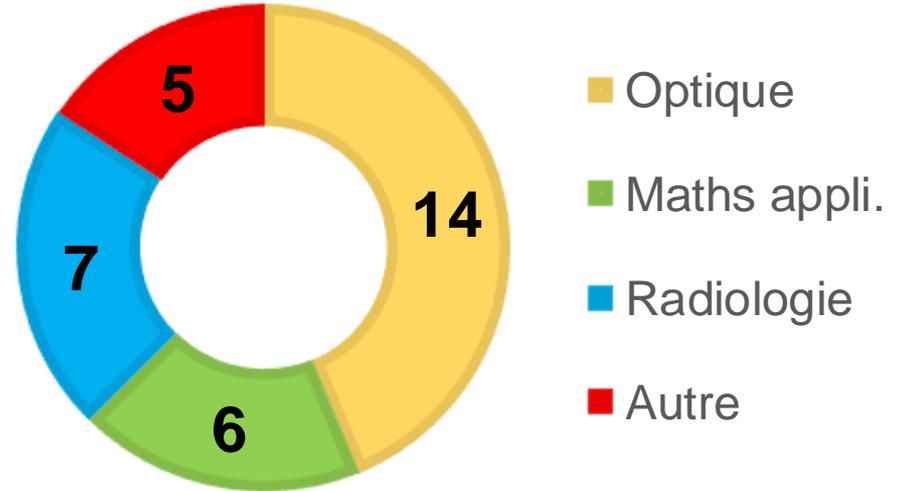


JFPJ Abascal

Publications

35 articles de journaux
32 premier quartile (Q1)
12 en 1er auteur / 5 en 2e auteur
/ 7 en dernier auteur

27 actes de conférences
1 chapitre livre (en/fr)
1 brevet



Animation

JIONC Comité orga.	BISP Comité tech.	ISBI Comité orga. chair

Projets

ANR PRC
IUF
ANR JCJC
UFI Vinci

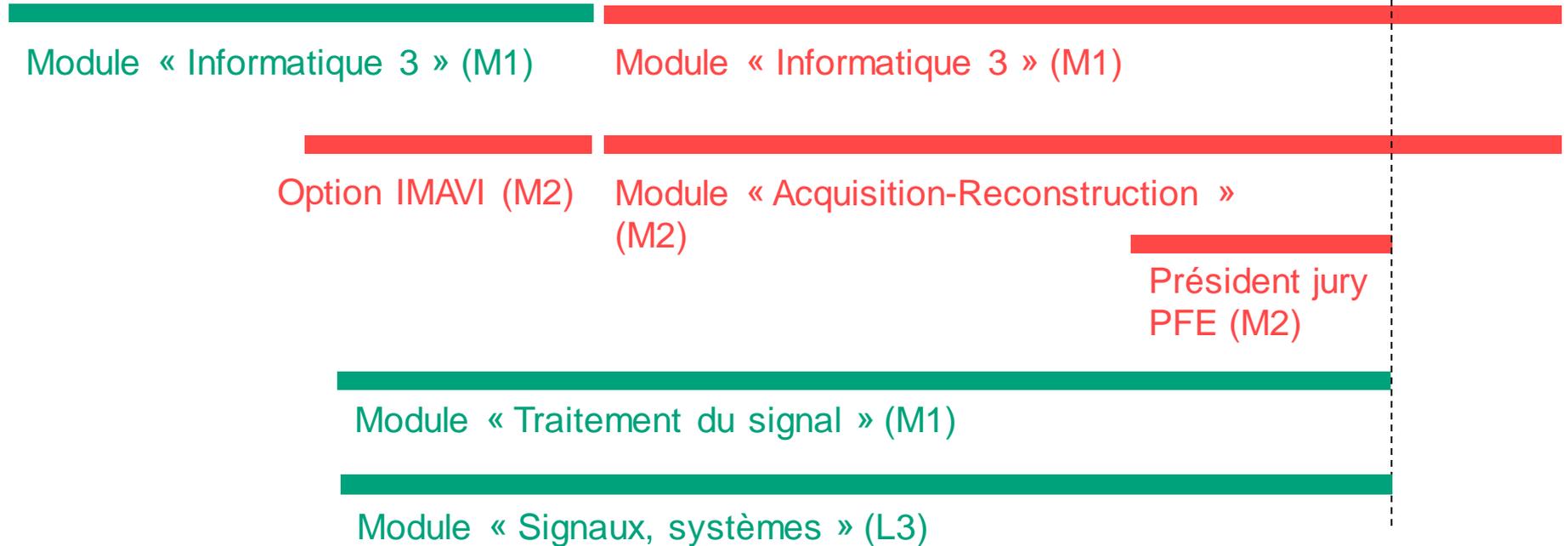
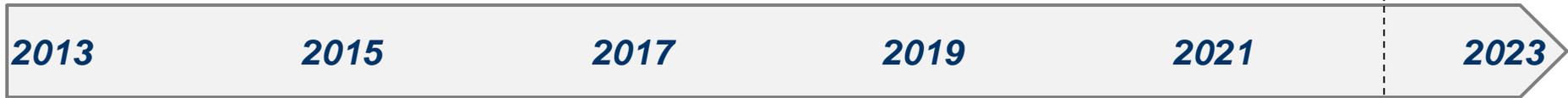
~900 k€



Intervenant
Responsable

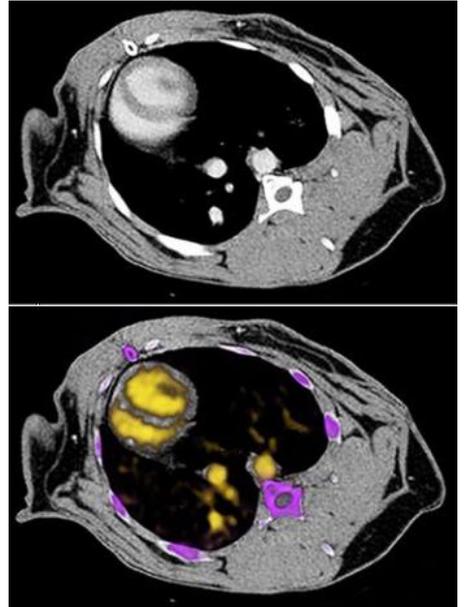
~220 heures/an

~70 h/an



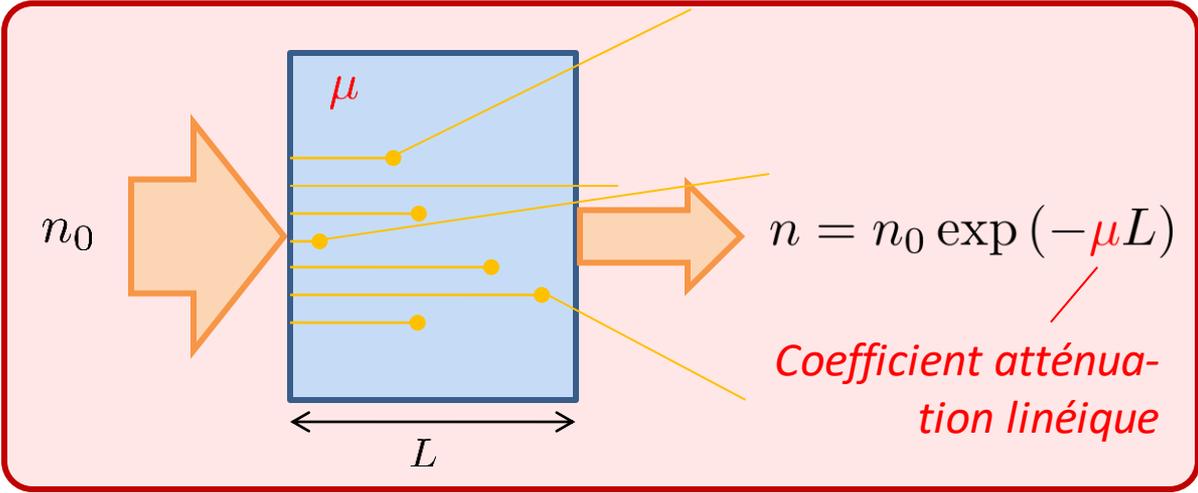
Tomodensitométrie spectrale

Iode → os
Or → réseau sanguin

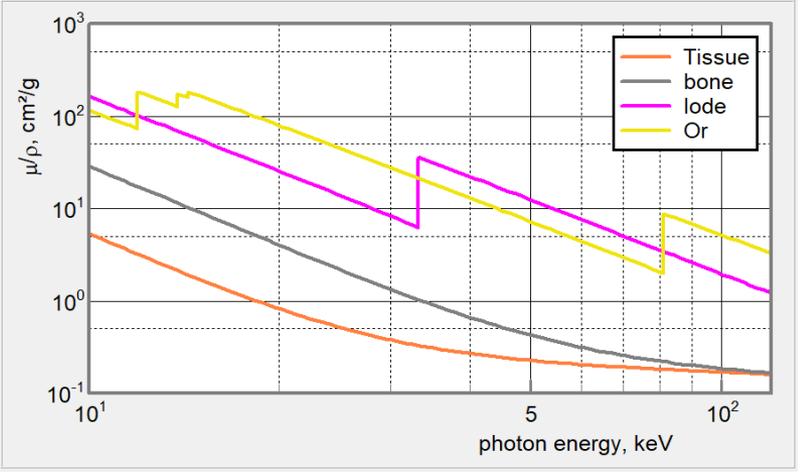


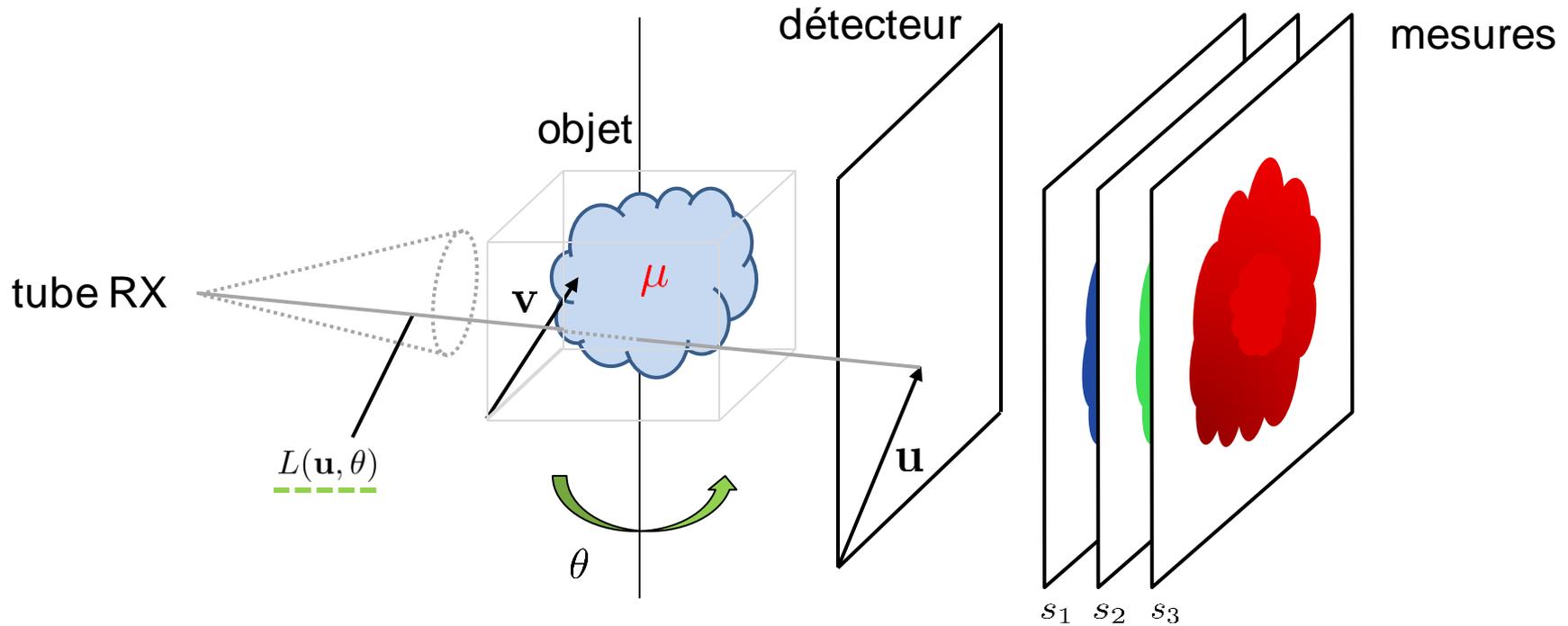
[D.P. Cormode *et al.* Sci. Rep. 7, 4784 (2017)]

[J M. Boone and A E. Chavez. Medical Physics 23, (1996)] via the XmuDat software.

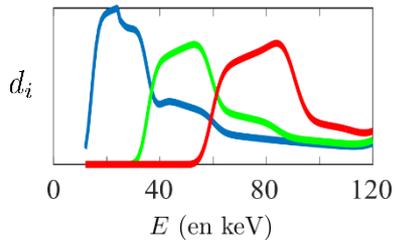


Coefficient d'att'enuation massique (tau = mu/rho)



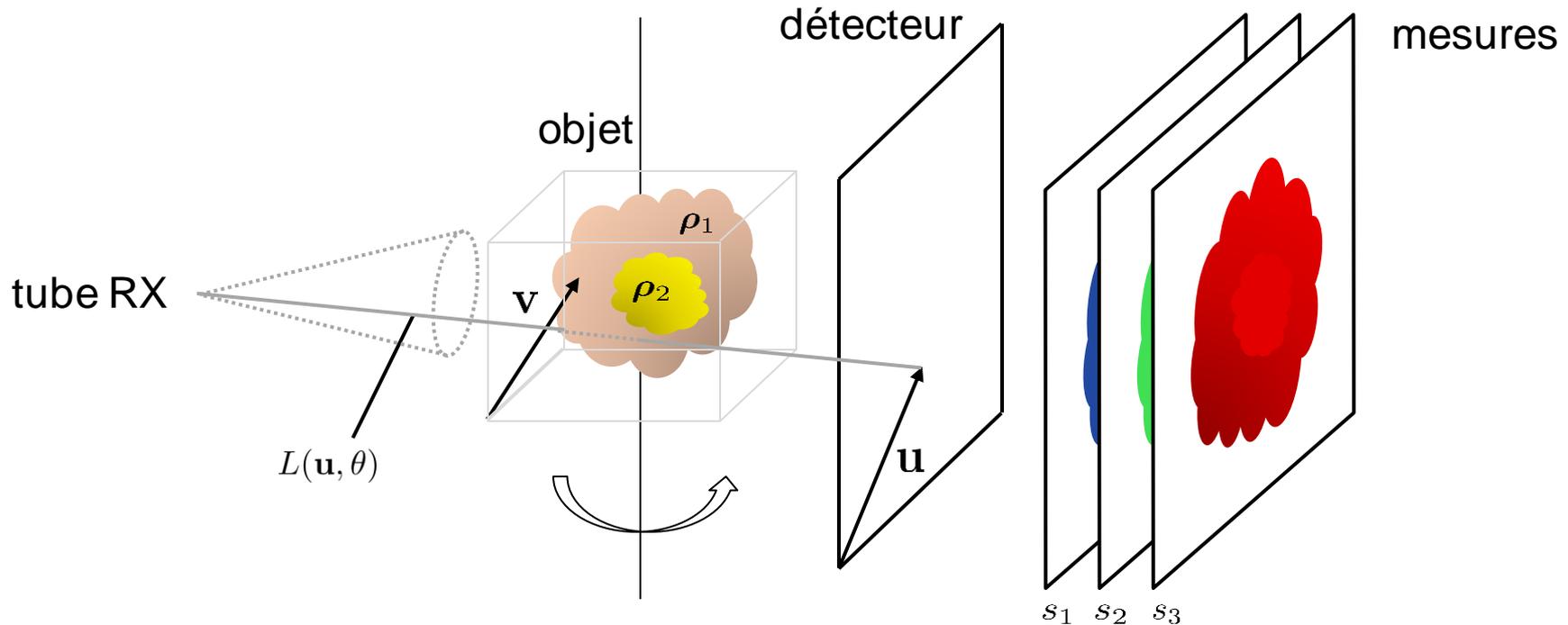


[Schlomka *et al.*, Phys. Med. Biol. **53**, 2008]



$$n_0(E) \exp \left[- \int_{L(\mathbf{u}, \theta)} \mu(\mathbf{v}, E) d\mathbf{v} \right]$$

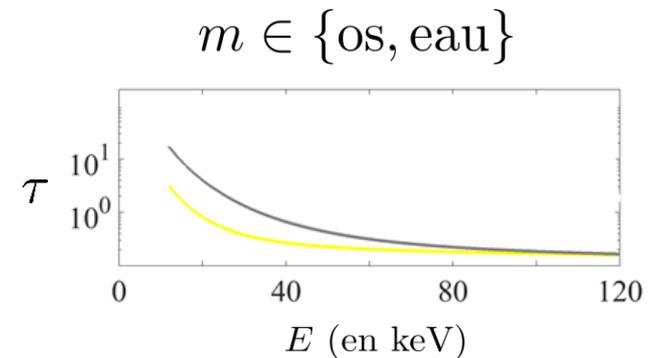
détecteur / source

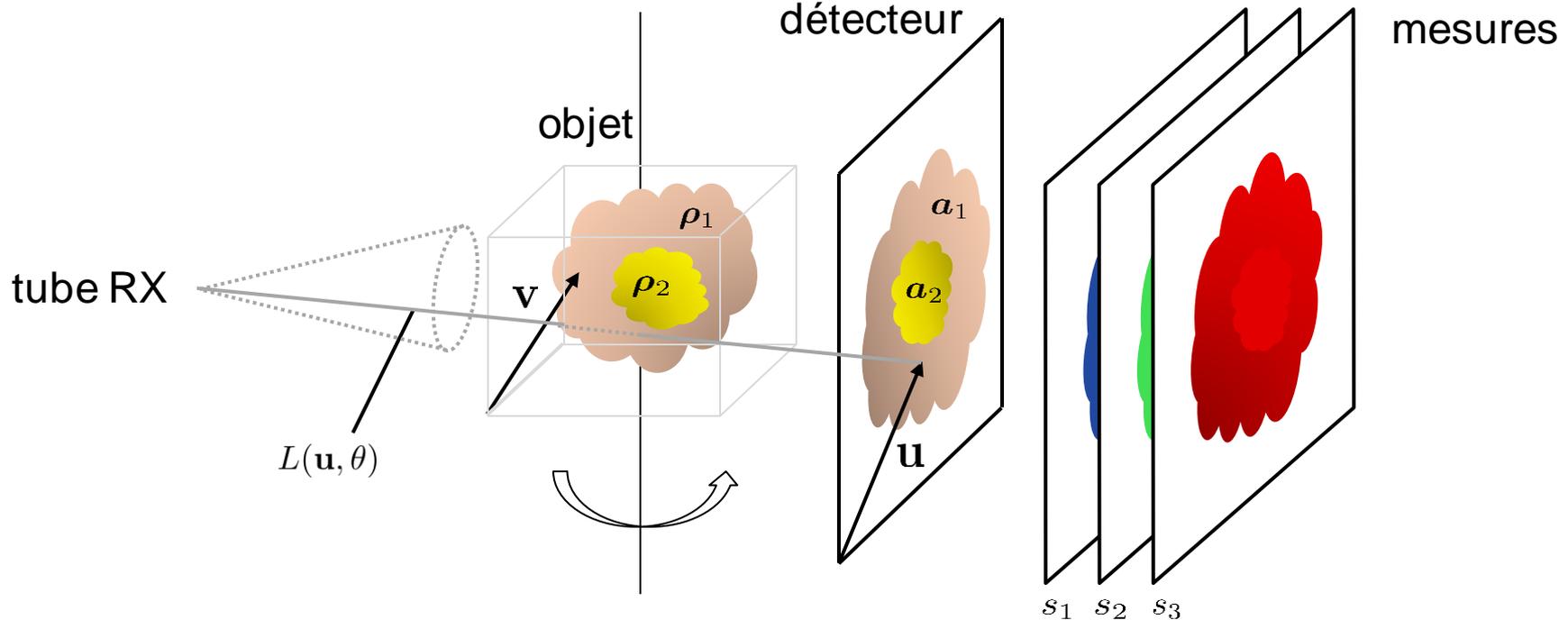


M matériaux constitutifs

$$\mu(\mathbf{v}, E) = \sum_{m=1}^M \mu_m(\mathbf{v}, E) = \sum_m \rho_m(\mathbf{v}) \tau_m(E)$$

[R E Alvarez and A Macovski. *Phys.Med.Biol.* 21 (1976)]



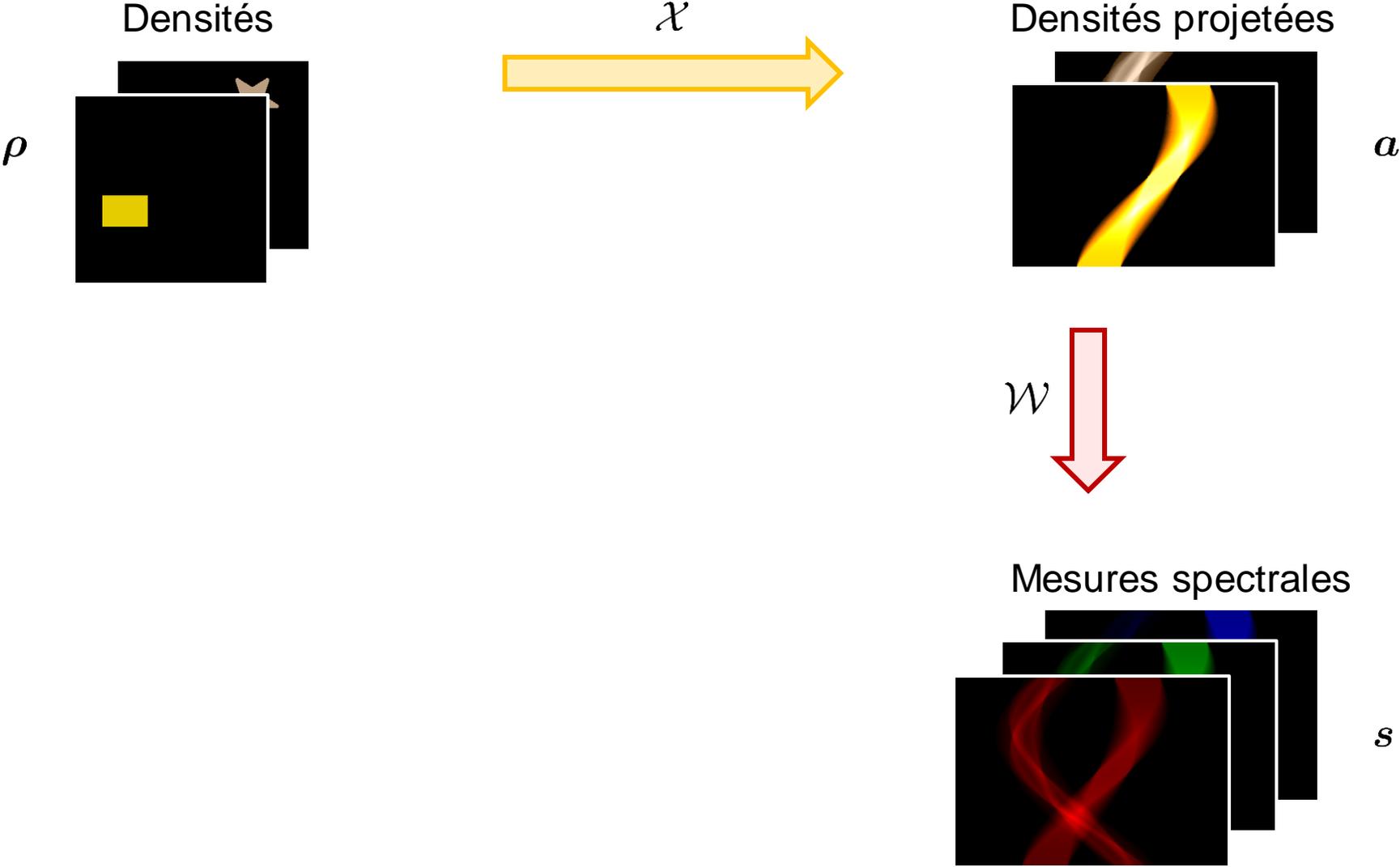


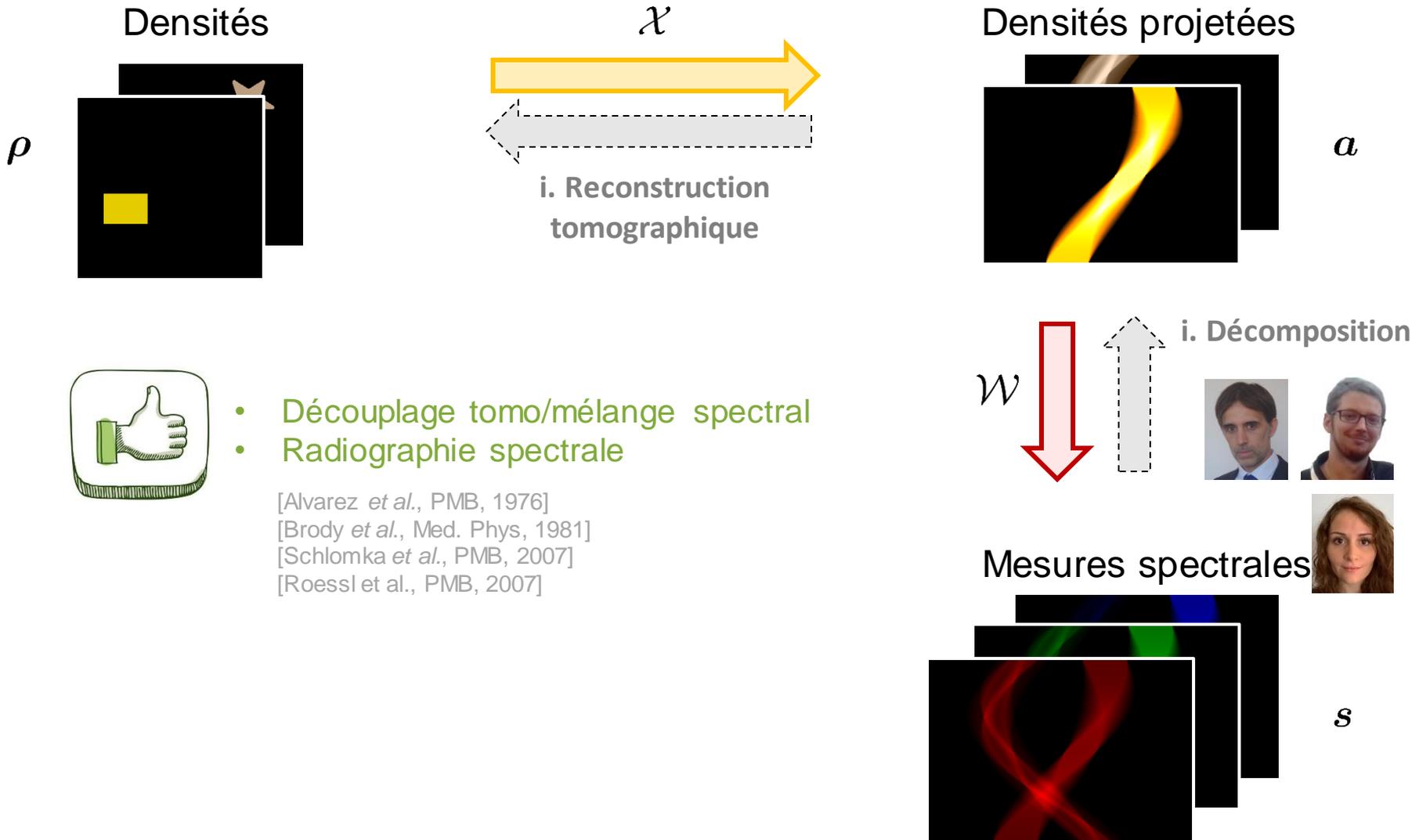
Mélange spectral par projection

$$s_i(\mathbf{u}, \theta) = \int_{\mathbb{R}} d_i(E) n_0(E) \exp \left[- \sum_{m=1}^M a_m(\mathbf{u}, \theta) \tau_m(E) \right] dE$$

Mélange spatial ("tomo") par matériau

$$a_m(\mathbf{u}, \theta) = \int_{L(\mathbf{u}, \theta)} \rho_m(\mathbf{v}, E) d\mathbf{v}$$





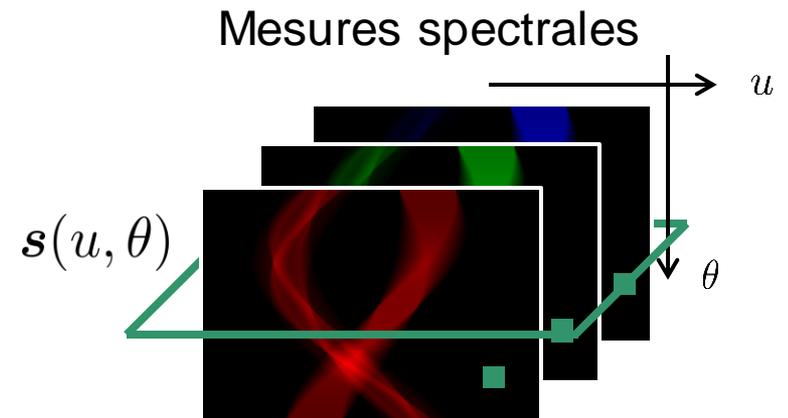
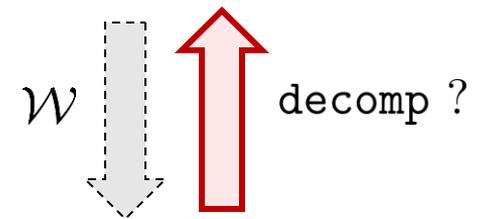
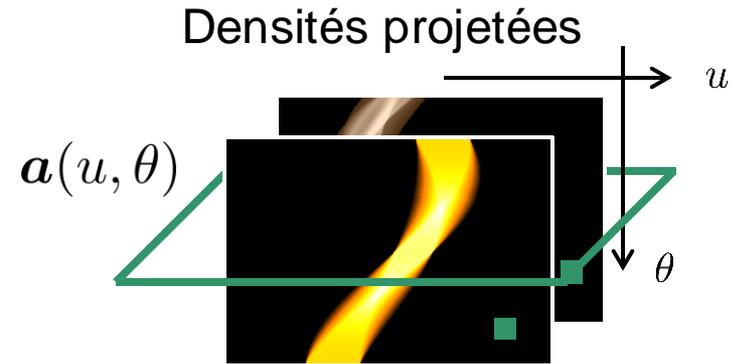
- Découplage tomo/mélange spectral
- Radiographie spectrale

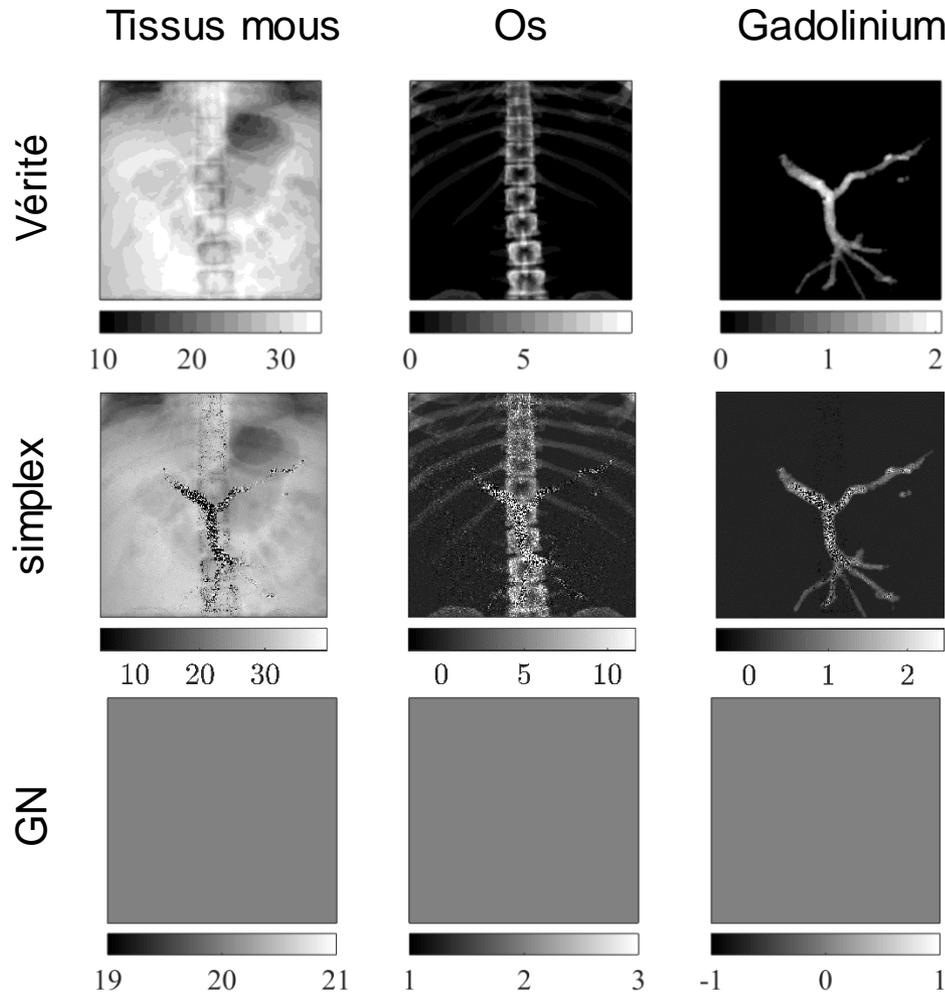
[Alvarez *et al.*, PMB, 1976]
[Brody *et al.*, Med. Phys, 1981]
[Schlomka *et al.*, PMB, 2007]
[Roessl *et al.*, PMB, 2007]

Approche variationnelle

$$\min_{\mathbf{a}} \underbrace{\mathcal{D}(\mathbf{s}, \mathcal{W}(\mathbf{a}))}_{\text{Attache aux données}} + \alpha \underbrace{\mathcal{R}(\mathbf{a})}_{\text{A priori}}$$

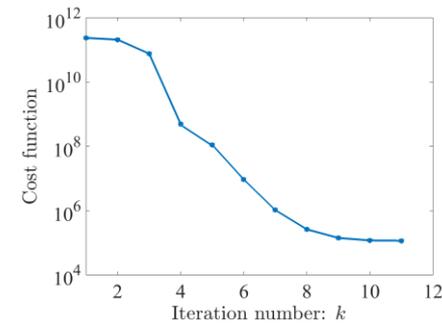
*pour un pixel
détecteur/angle de
vue/sinogramme*





Algorithme de Gauss-Newton (GN)

$$\mathbf{a}^{(k+1)} = \mathbf{a}^{(k)} + \lambda^{(k)} \delta \mathbf{a}^{(k)}$$



Init: $a_{\text{soft}}^0 = 20 \text{ g.cm}^{-2}$
 $a_{\text{bone}}^0 = 2 \text{ g.cm}^{-2}$
 $a_{\text{Gd}}^0 = 0 \text{ g.cm}^{-2}$

[N. Ducros *et al.*, Med. Phys. **44**, 2017]

[JFJP Abascal *et al.*, Inverse Probl. **34**, 2018]

$$\min_{\mathbf{a}} \underbrace{\mathcal{D}(\mathbf{s}, \mathcal{W}(\mathbf{a}))}_{\text{Attache aux données}} + \alpha \underbrace{\mathcal{R}(\mathbf{a})}_{\text{A priori}} + \mathcal{R}_2(\mathbf{a})$$

$$\mathcal{R}_2(\mathbf{a}) = \begin{cases} 0 & \text{si } \mathbf{b}_1 \leq \mathbf{a} \leq \mathbf{b}_2 \\ \infty & \text{sinon} \end{cases}$$

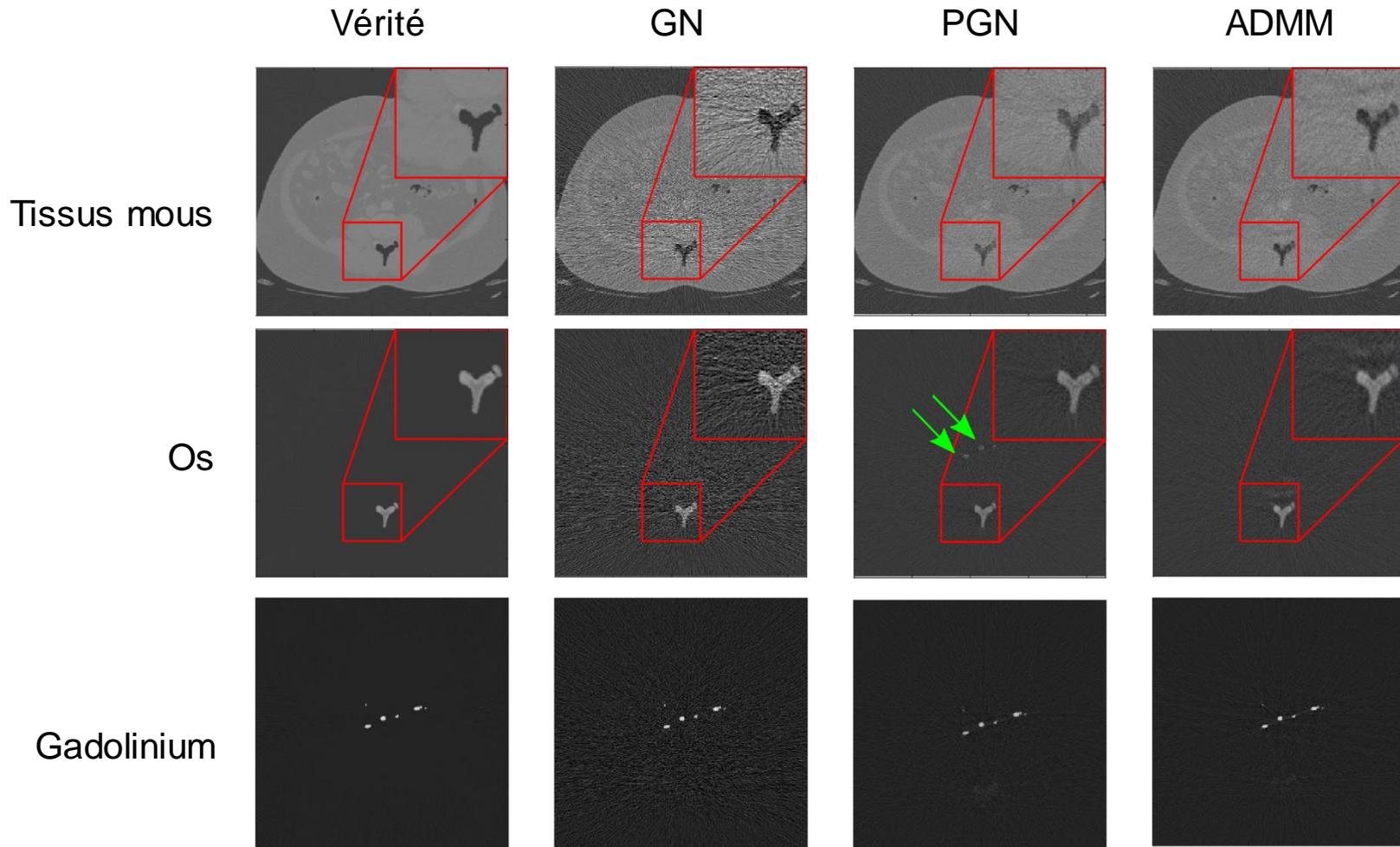
Algorithme de Gauss-Newton projeté (PGN)

[T. Hohweiller *et al.*, IEEE ISBI, 2018]

$$\mathcal{R}_2(\mathbf{a}) = \begin{cases} 0 & \text{si } \mathbf{0} \leq \mathbf{a} \text{ et } \mathbf{a}_{\text{gd}}^{\top} \mathbf{1} = c \\ \infty & \text{sinon} \end{cases}$$

Algorithme des directions alternées (ADMM)

[T. Hohweiller *et al.*, EUSIPCO, 2018]

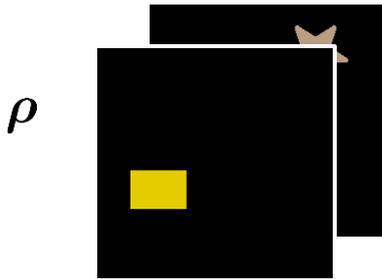


$b_1 = 0$ et $b_2 = \infty$

$c = c_{\text{vrai}}$

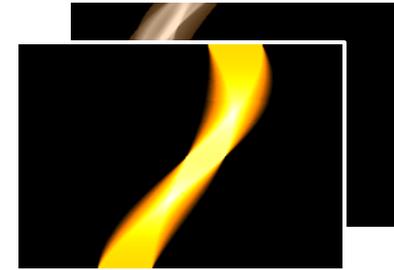
[T. Hohweiller, Thèse de doctorat, 2019]

Densités

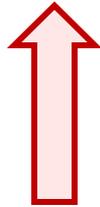


$$\rho^* = \text{tomo}(a^*)$$

Densités projetées

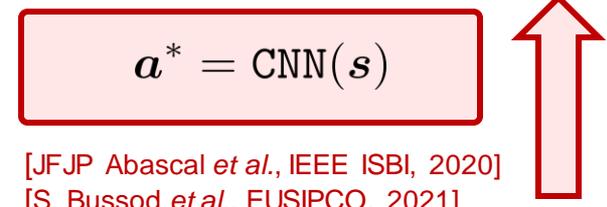


a



$$\rho^* = \text{CNN}(r)$$

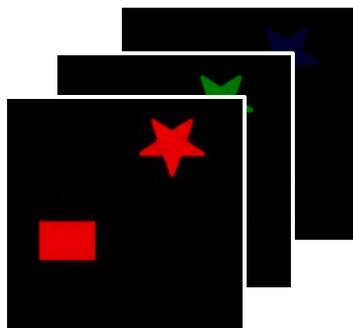
[JFJP Abascal *et al.*, IEEE Access **9**, 2021]



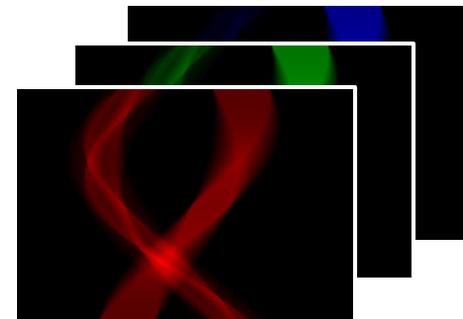
$$a^* = \text{CNN}(s)$$

[JFJP Abascal *et al.*, IEEE ISBI, 2020]
[S. Bussod *et al.*, EUSIPCO, 2021]

Mesures spectrales



$$r = \text{tomo}(s)$$



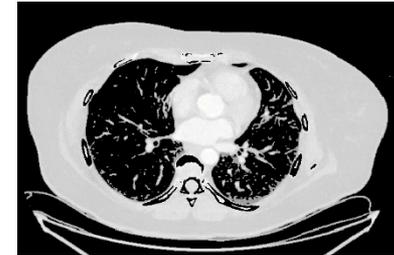
s

Vérité

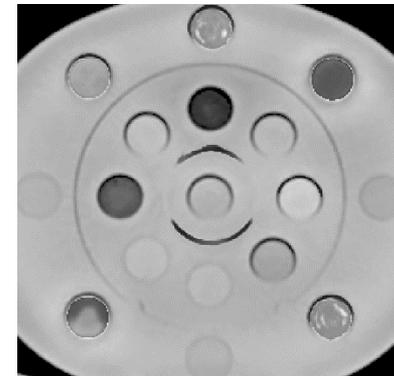
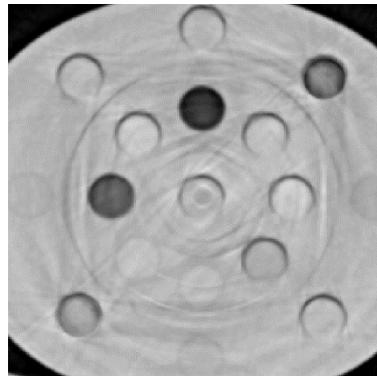
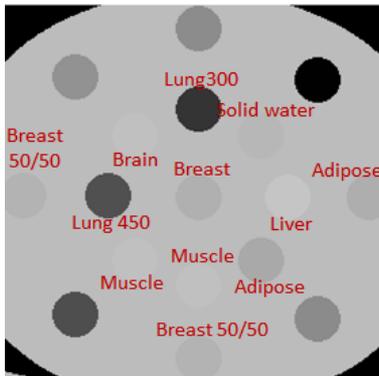
GN

CNN

Simulations



Données réelles



[JFJP Abascal *et al.*, IEEE Access **9**, 2021]

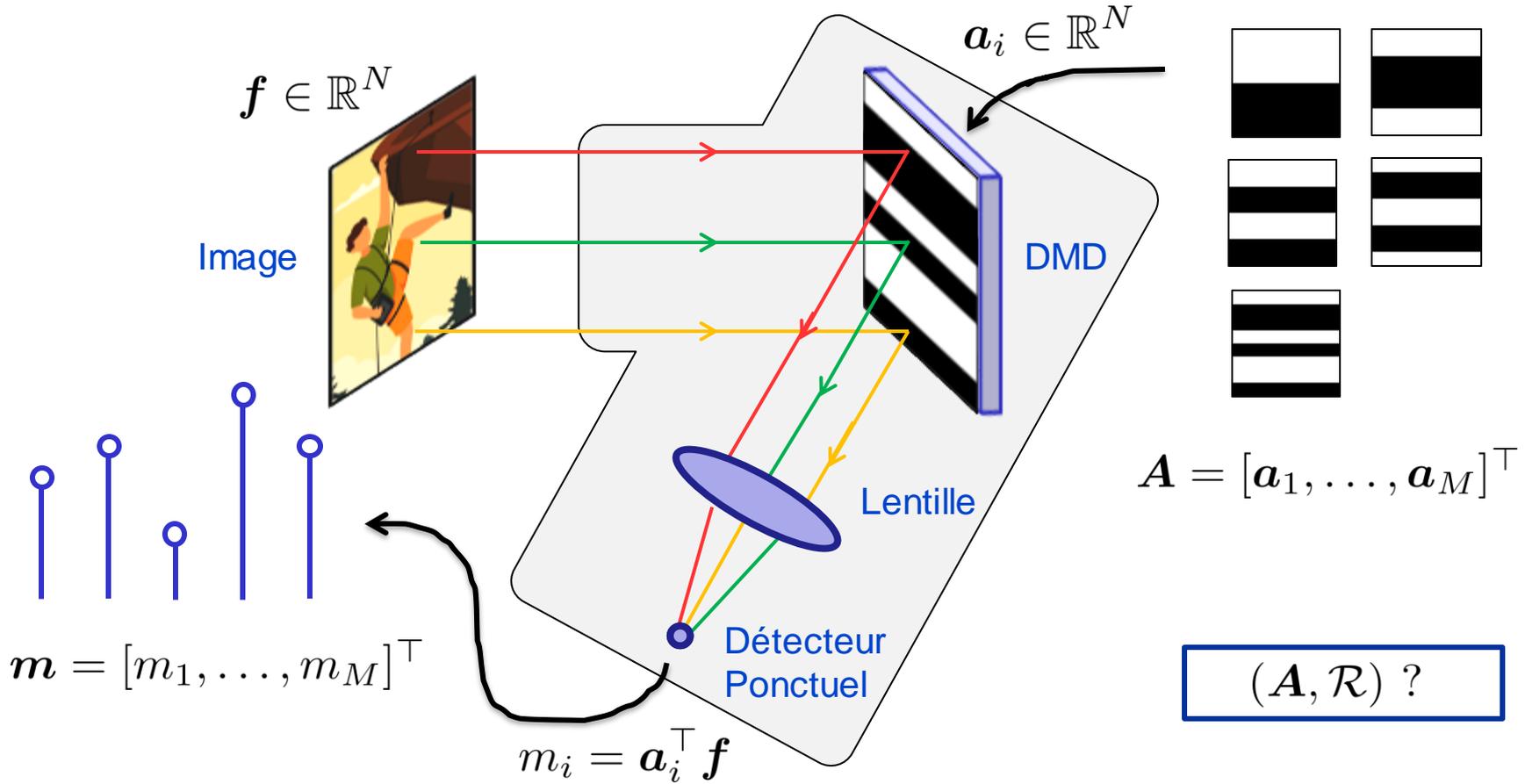


- Qualité image (domaine des projections et image)
- Rapidité (x40)



- Interprétation/garanties théoriques
- Robustesse aux écarts au modèle

Imagerie monodétecteur (*single-pixel imaging*)



Acquisition

$$\mathbf{m} = \mathbf{A}\mathbf{f}$$

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

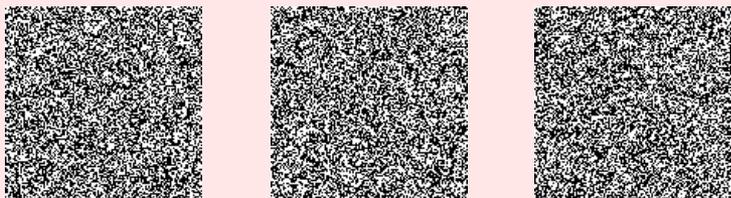
Reconstruction

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

$$\mathcal{R}: \mathbb{R}^M \rightarrow \mathbb{R}^N$$

Comment choisir la paire acquisition–reconstruction (A, R) quand $M \ll N$?

Aléatoire (par ex. Bernouilli $\frac{1}{2}$)



Minimisation L1 (typ.)

$$\min_f \|m - Af\|_2^2 + \lambda \|\Phi f\|_1$$



Single-Pixel Imaging via Compressive Sampling

[Building simpler, smaller, and less-expensive digital cameras]



Original
(256x256)

1300
mes., x50

6500
mes., x10

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

Réseau de neurones

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



Entraînement long (~heures, jours)



Inférence rapide, ~millisecondes, secondes

SCIENTIFIC REPORTS

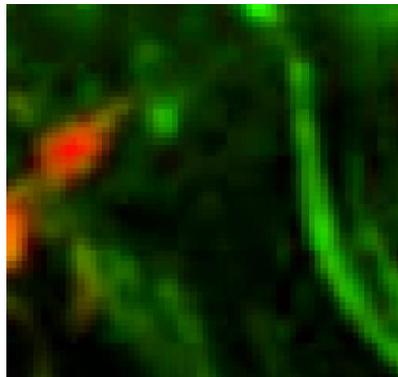
OPEN **Deep learning for real-time single-pixel video**

Catherine F. Higham¹, Roderick Murray-Smith¹, Miles J. Padgett² & Matthew P. Edgar²

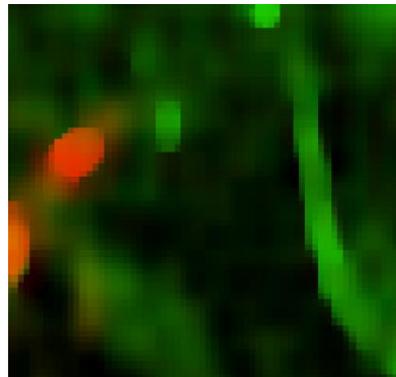
[C. Higham *et al.*, *Scient. Reports*, 2018]

microscopie de fluorescence
(mélanomes et vaisseaux)

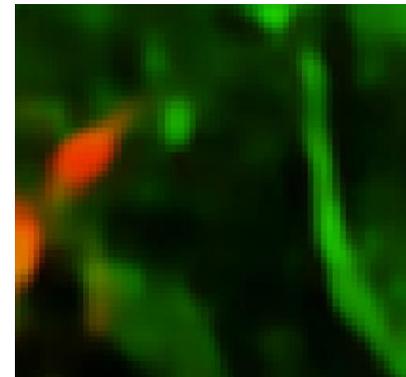
Vérité



Variation totale (L1)



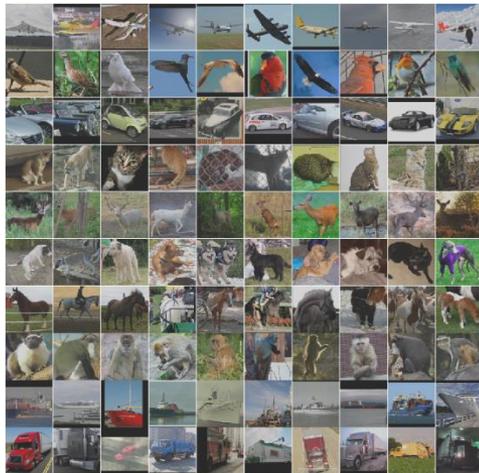
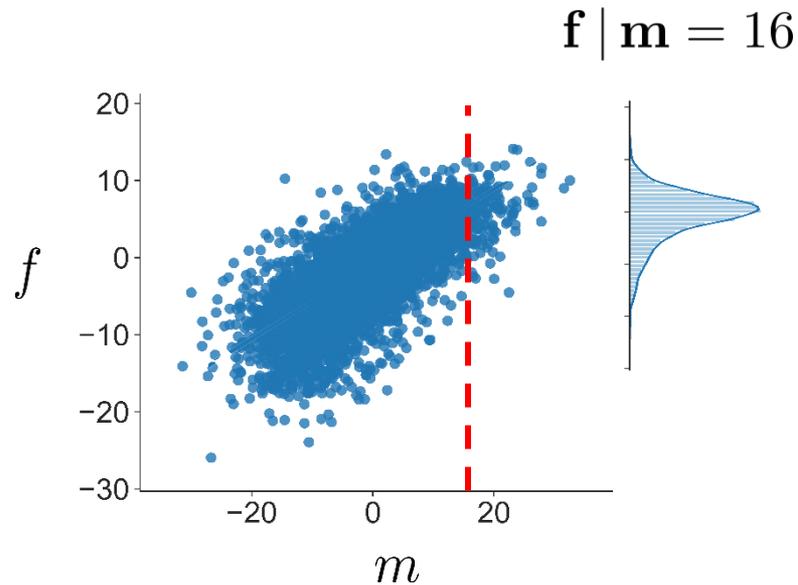
Réseau neurones



red: TV + 0.8 dB

green: TV + 1.16 dB

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

 $\{\mathbf{f}^{(\ell)}\}_{1 \leq \ell \leq L}$ 

Espérance
conditionnelle

$$\begin{aligned} \mathcal{R}(\mathbf{m}) \\ = \\ \mathbb{E}(\mathbf{f} \mid \mathbf{m} = \mathbf{m}) \end{aligned}$$

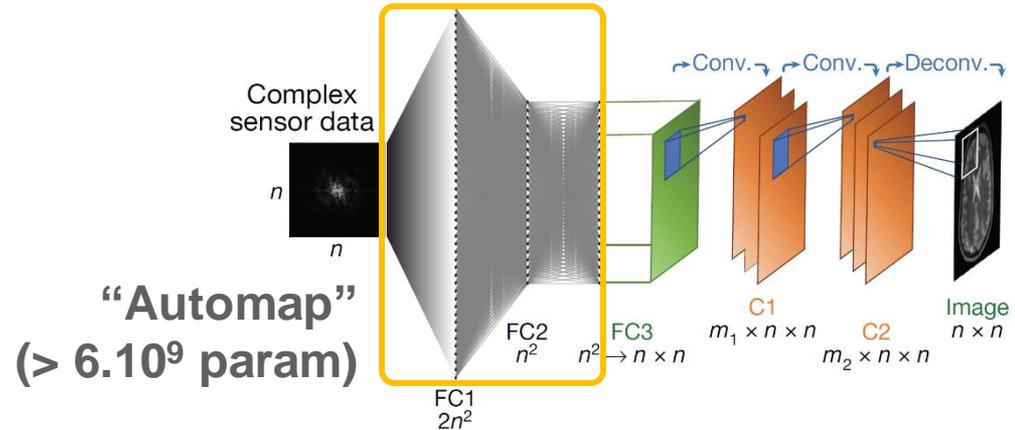
Moindre erreur quadratique moyenne
(MMSE)

$$\mathcal{R}(\mathbf{m}) \in \arg \min_{\mathcal{R}: \mathbb{R}^M \rightarrow \mathbb{R}^N} \frac{1}{L} \sum_{\ell} \|\mathcal{R}(\mathbf{m}^{\ell}) - \mathbf{f}^{\ell}\|_2^2$$

Par restriction

$$\arg \min_{\theta} \frac{1}{L} \sum_{\ell} \|\mathcal{R}(\theta; \mathbf{m}^{\ell}) - \mathbf{f}^{\ell}\|_2^2$$

Choix de \mathcal{R} ?



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

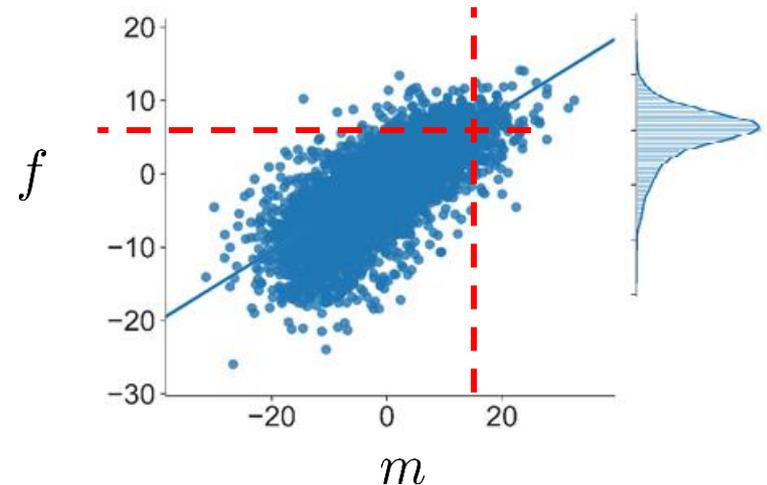
Cas Gaussien / MMSE Linéaire

$$\mathcal{R}(m) = Wm + b,$$

$$f^* = \Gamma \Sigma^{-1} m$$

Covariance
entre mesures
et image

Covariance des
mesures

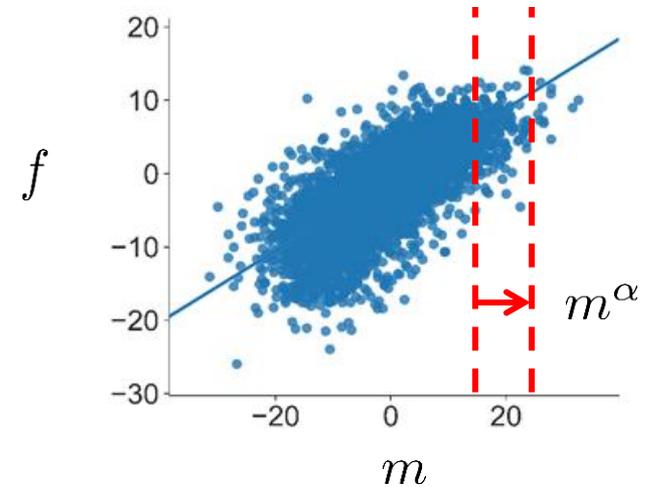


[N. Ducros et al., IEEE ISBI, 2020]

En présence de bruit

$$\mathbf{m}_\alpha = \mathbf{m} + \mathbf{e}_\alpha$$

$$\mathbf{f}^*(\mathbf{m}^\alpha) = \mathbb{E}(\mathbf{f} \mid \mathbf{m}^\alpha = \mathbf{m}^\alpha)$$

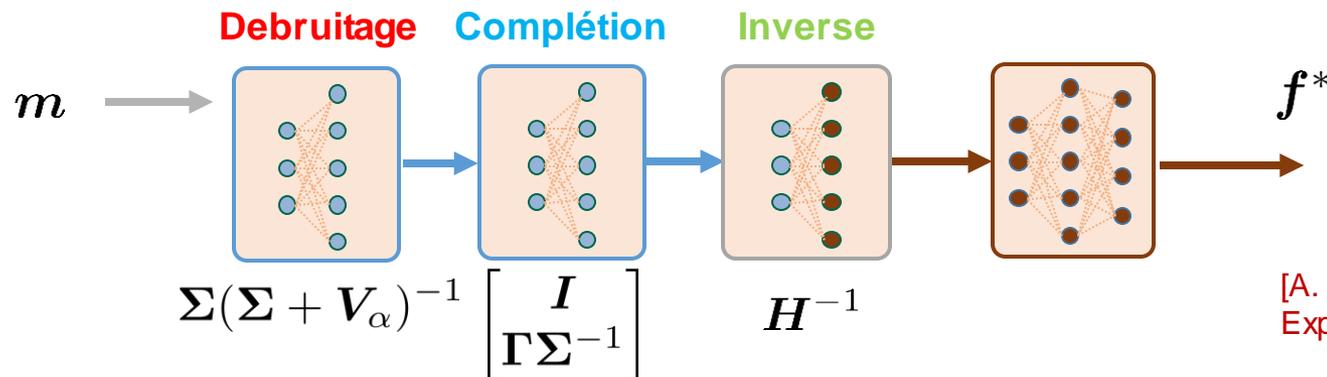


Réseau débruitage complétion (DC-Net)

$$\mathbf{f}^* = \mathcal{R}_\theta(\mathbf{m}) = \mathcal{G}_\theta(\underbrace{\mathbf{H}^{-1}}_{\text{Inverse}} \underbrace{\mathbf{C}}_{\text{Complétion}} \underbrace{\mathbf{D}_\alpha}_{\text{Debruitage}} \mathbf{m})$$

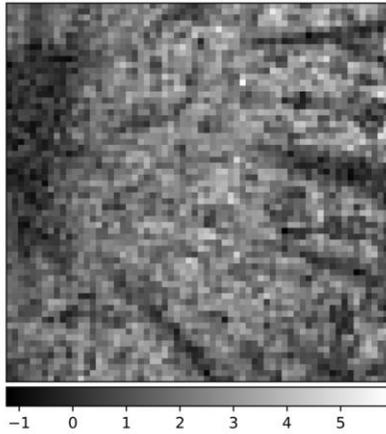
Sous échantillonnage

$$\mathbf{A} = \begin{bmatrix} \mathbf{I}_M & \mathbf{0} \end{bmatrix} \mathbf{H}$$

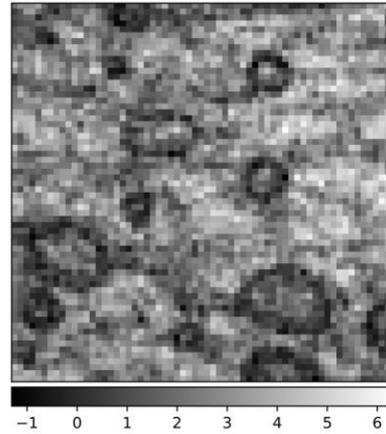


[A. Lorente Mur *et al.* Opt Express **29**, 17097 (2021)]

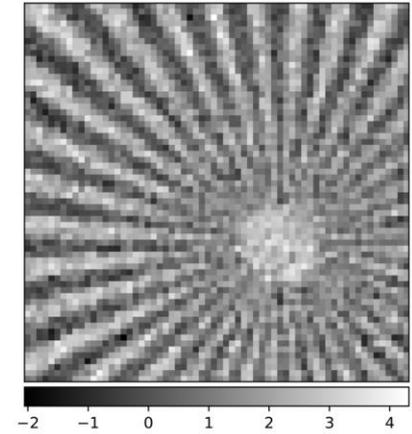
Tomato (x1 zoom)



Tomato (x12 zoom)



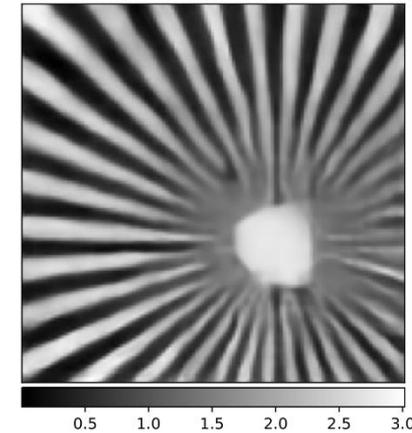
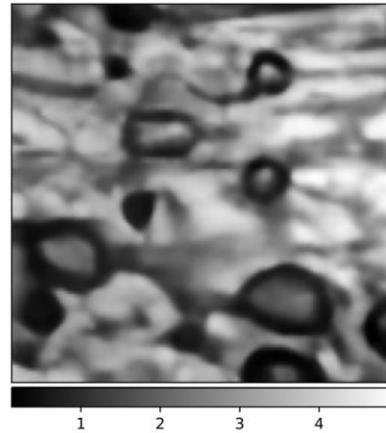
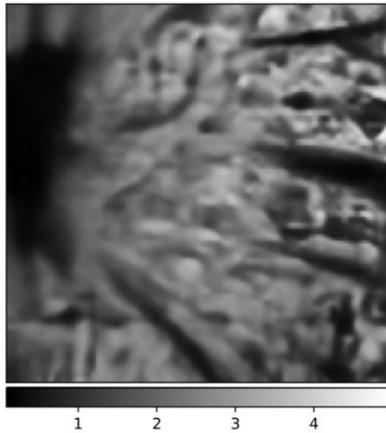
Star Sector (x12 zoom)



pseudoinverse

$$H^{-1} \begin{bmatrix} m \\ 0 \end{bmatrix}$$

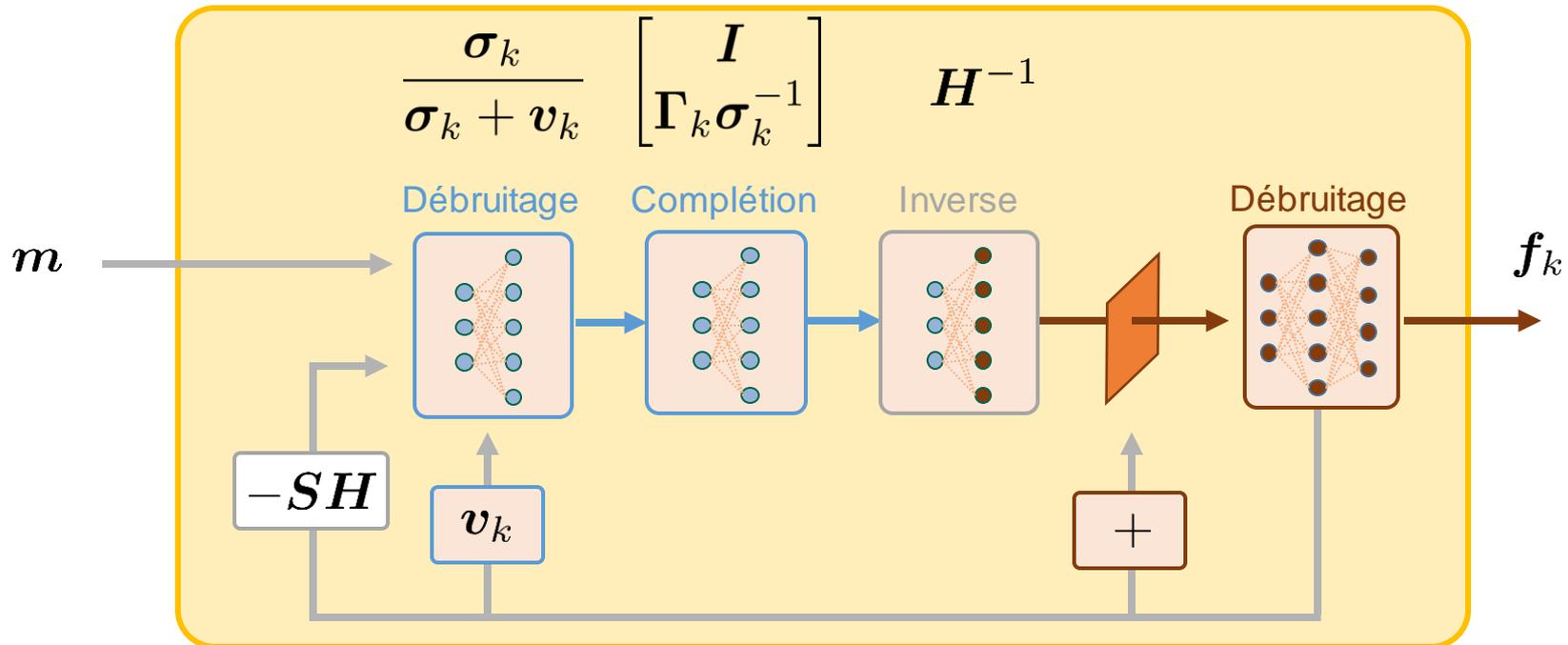
DC-Net



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

Algorithme itératif $\mathcal{R}_\theta(\mathbf{m}) = \mathbf{f}_K$

[S. Arridge *et al.*, Acta Numerica (2019)]
 [G. Barbastathis *et al.*, Optica, (2019)]

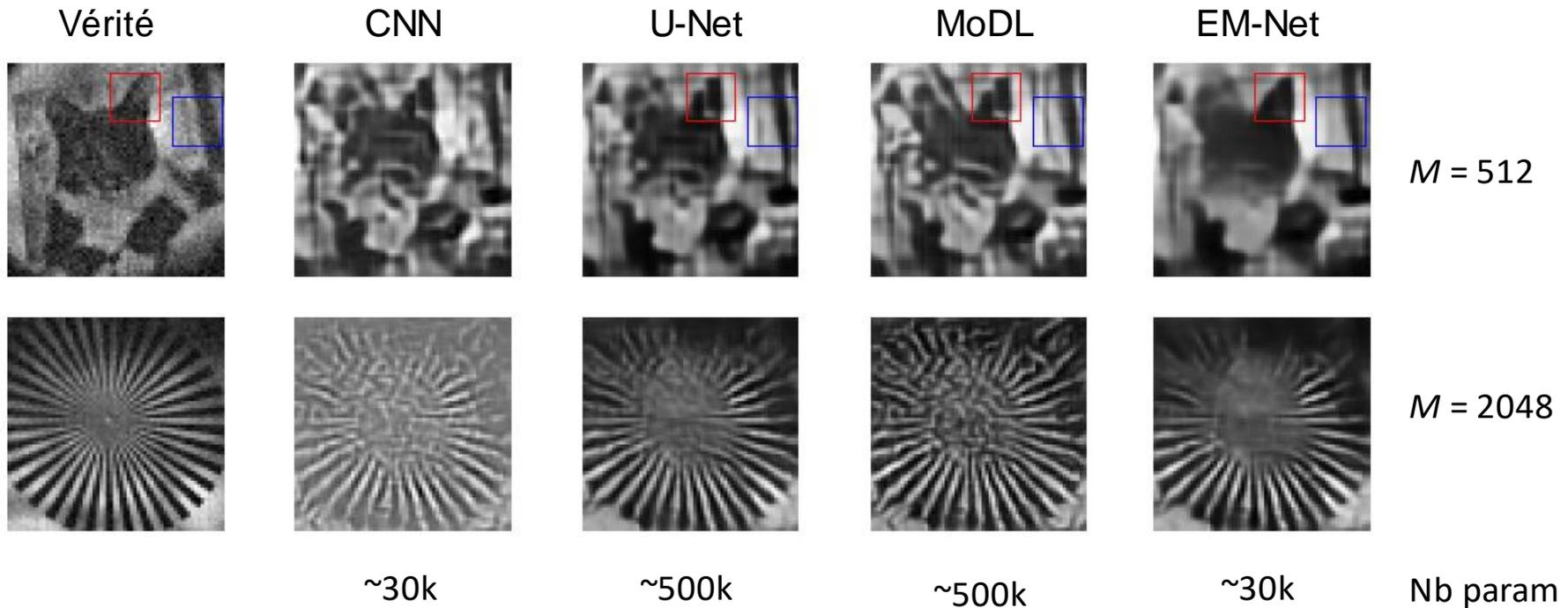


Maximum a posteriori

$$\max_{\mathbf{f}} \log p(\mathbf{m}|\mathbf{f}) + \log p(\mathbf{f})$$

[Lorente-Mur *et. al.*, IEEE ISBI, 2021]
 [Lorente-Mur *et. al.*, IEEE TCI, 2022]

➤ **Données expérimentales ($N = 64 \times 64 = 4096$)**



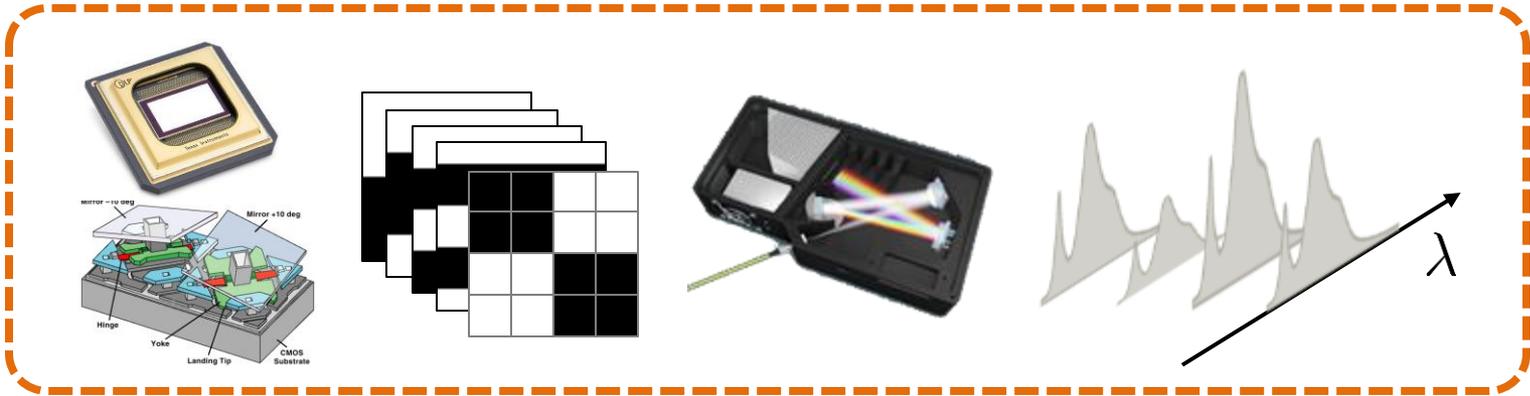
[Lorente-Mur *et. al*, IEEE TCI, 2022]

‘(...) 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.’

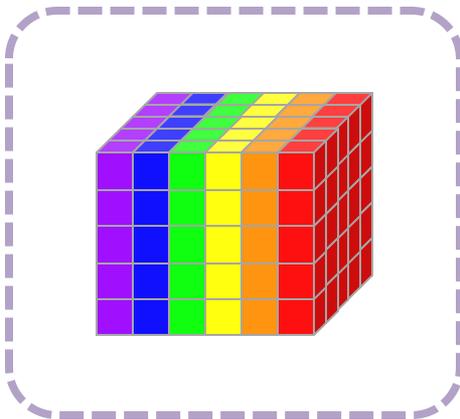
[J. Shenouda and W.U. Bajwa. IEEE Signal Process. Mag. **40**, 141 (2023)]

<https://github.com/openspyrit/>

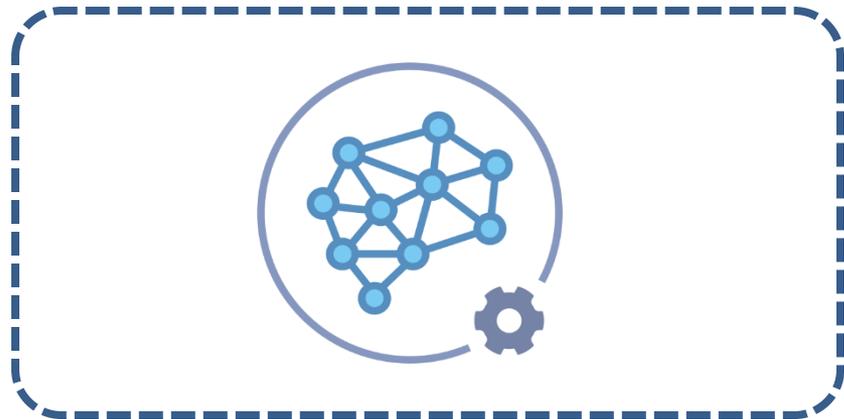
spas



spihim



spyrit

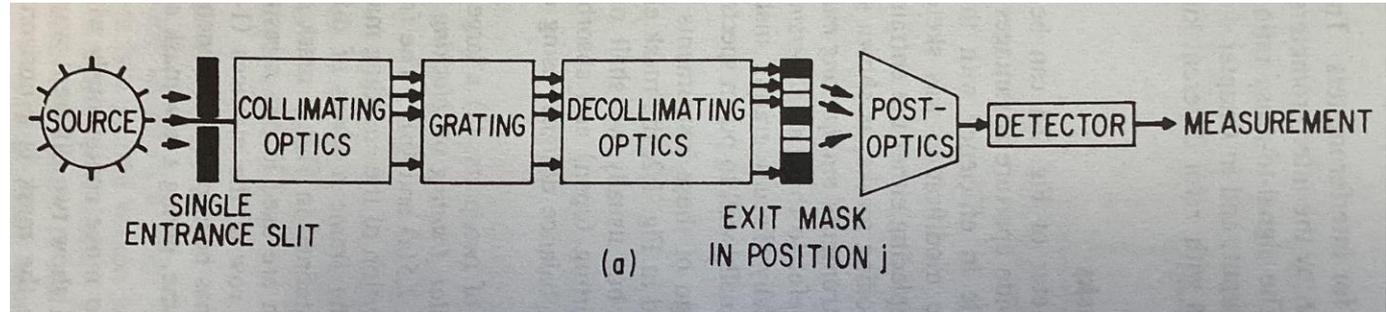


[G. Beneti *et al.* Opt Express **31**, 15599 (2023)]

Travaux en cours et perspectives

HADAMARD TRANSFORM OPTICS

Martin Harwit
Neil J.A. Sloane

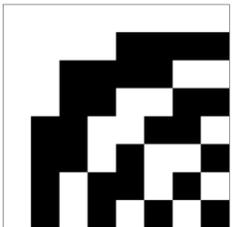


[M. Harwit and N
Sloane, Academic
Press, 1979]

*'(...) conventional spectrometer is modified by using a
mask to encode the light at the output'*

Hadamard

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



$$\mathbf{A}^T \mathbf{A} = N \mathbf{I}_N$$

Minimization L2

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

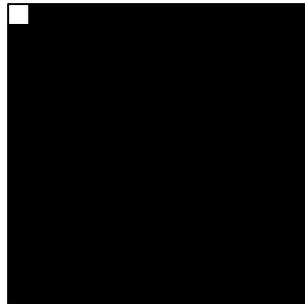
Avantage de Fellgett

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

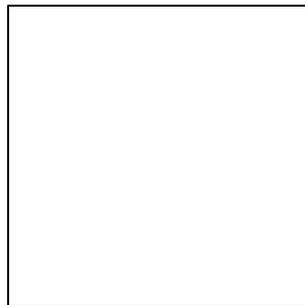
$$\text{var}(f_n^*) = \frac{1}{N} \sigma^2 < \sigma^2$$



Raster scan



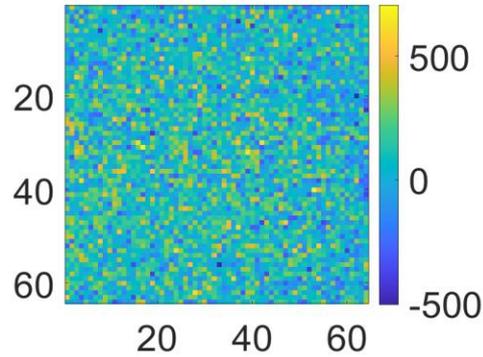
Hadamard scan



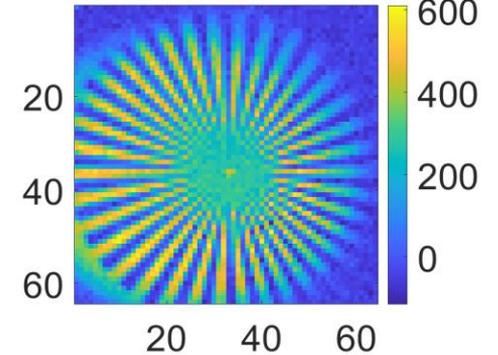
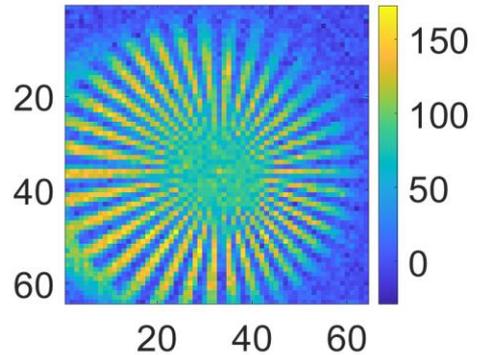
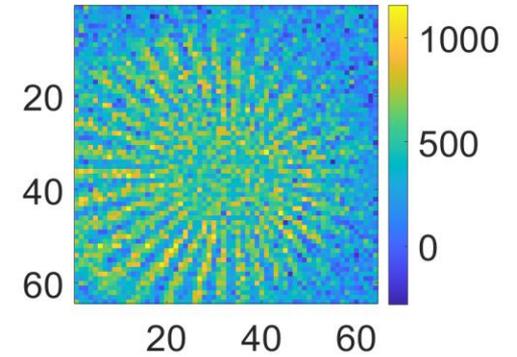
rapport signal-sur-bruit



signal x1



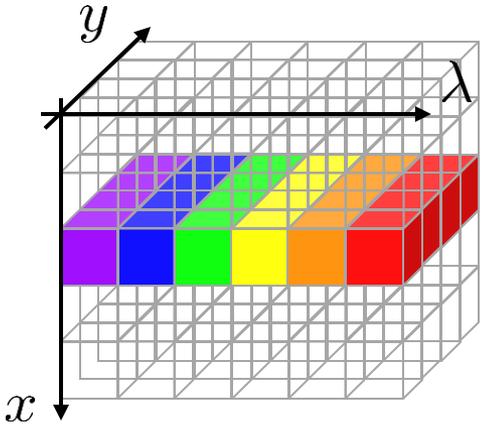
signal x4



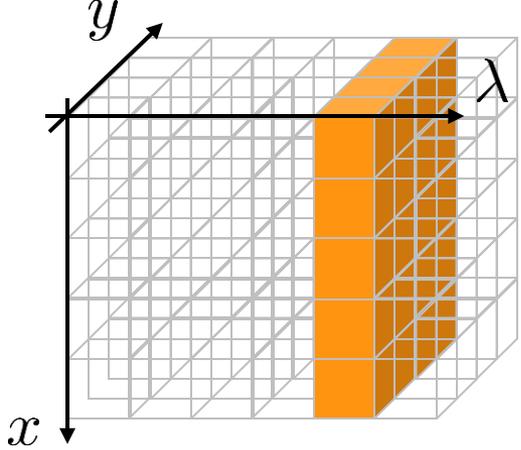
[N Ducros, unpublished results, 2020]

Effet physique = cadeau de la nature...

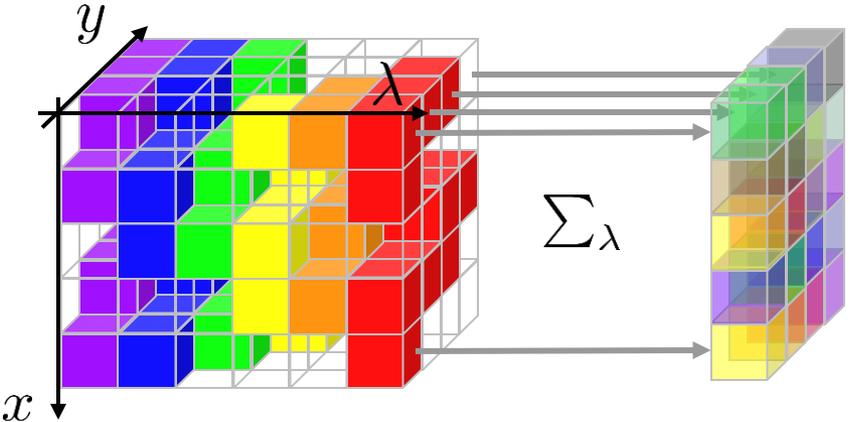
...Moins avantageux que la parallélisation



Pushbroom



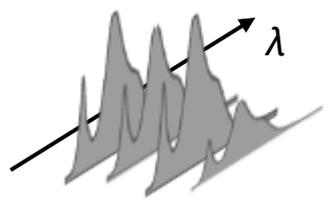
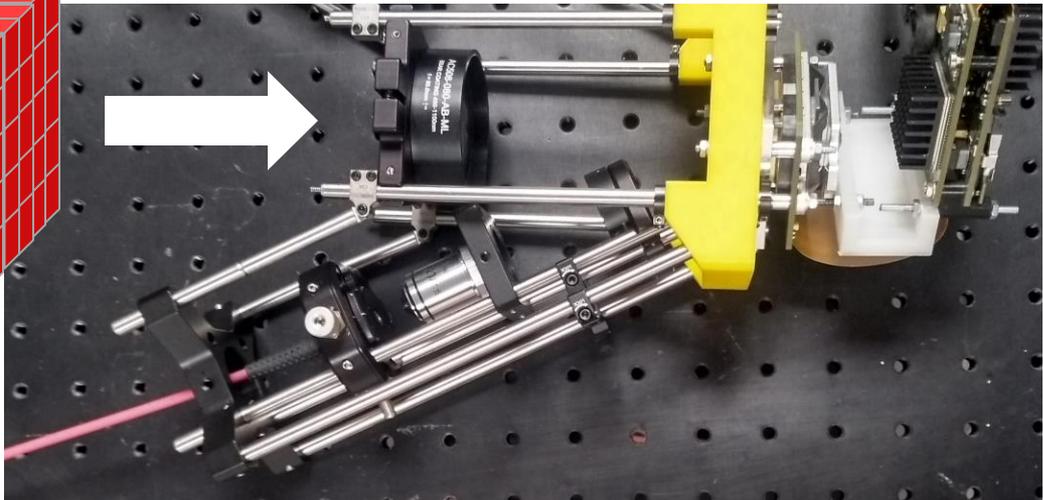
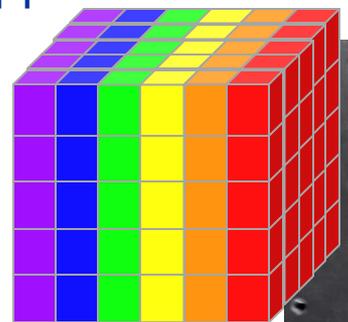
Filtre optique



Computational

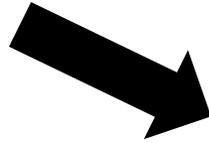


Résolution spatiale ++
Résolution temporelle ++

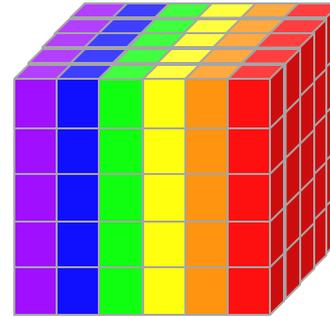


>200 hypercubes en accès libre
<https://github.com/openspyrit/spihim>

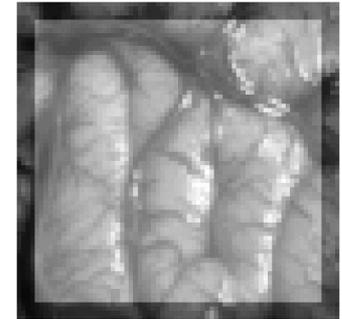
**Cube 64 × 64 × 2048
en 10 s**



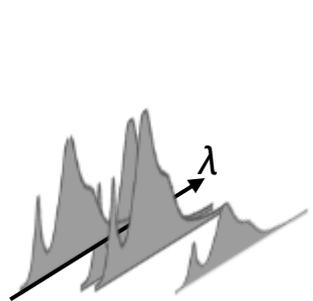
Résolution spatiale ++
Résolution temporelle ++



1. Résolution spatiale **et** spectrale ++

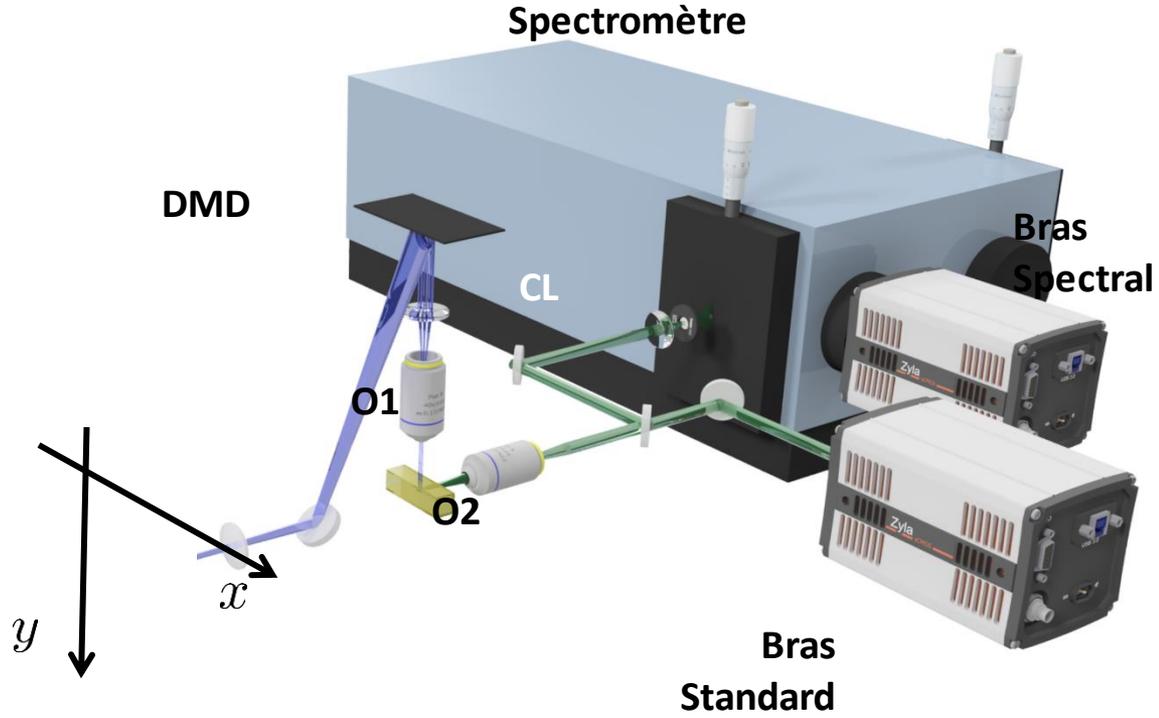
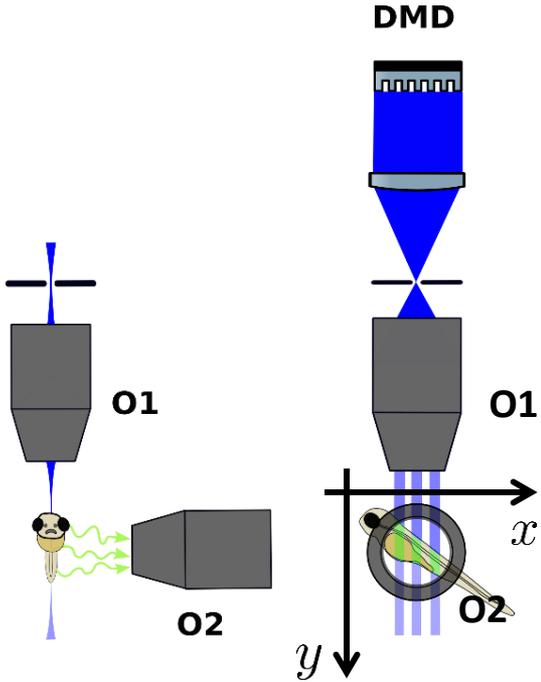


2. Résolution temporelle ++



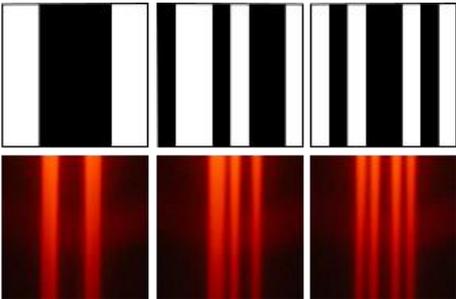
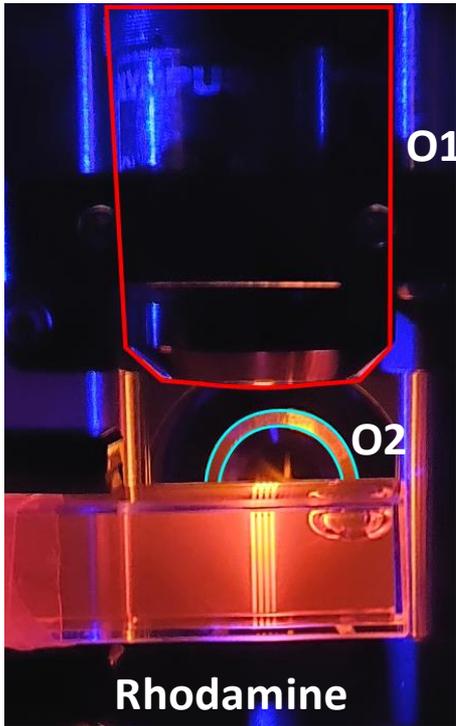
Résolution spectrale ++

3. SNR ++
(Optimiser le « budget temps »)

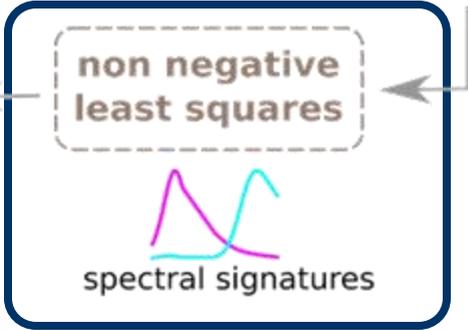
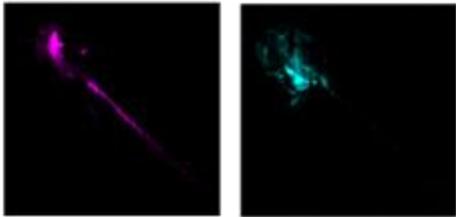
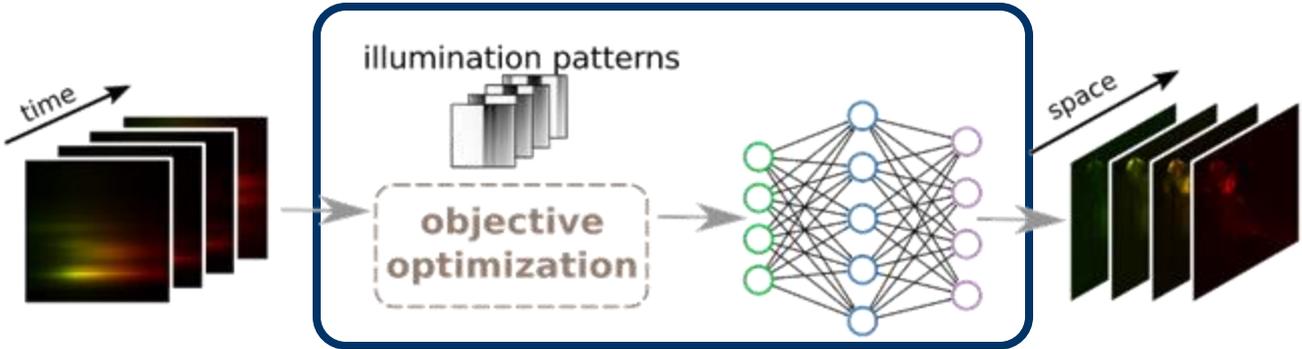


$$m_i(y, \lambda) = \int p_i(x) f(x, y, \lambda) dx, \quad 1 \leq i \leq M$$

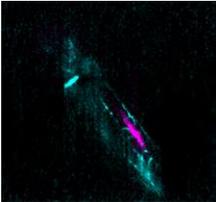
[S. Crombez et al. Opt. Express 30 (2022)]



Reconstruction

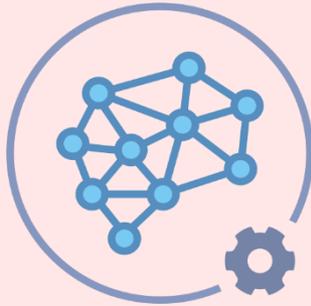


Démélange

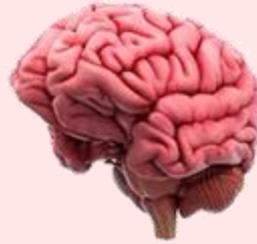


[S. Crombez *et al.*, unpublished (2024)]

$(x, y, z, \lambda, t, ?)$



IA



IN



HARDWARE

Merci !

CREATIS TOMORADIO

Thomas BAUDIER

Elie BRETIN

Jérémy COHEN

Chloé EXBRAYAT-HERITIER

Laurent MAHIEU-WILLIAME

Bruno MONTCEL

Françoise PEYRIN

Cédric RAY

Audrey REPETTI

Florence RUGGIERO

Michaël SDIKA