

MultiCore Fiber Interferometric Imaging

PoMM, Lille.

O. Leblanc.

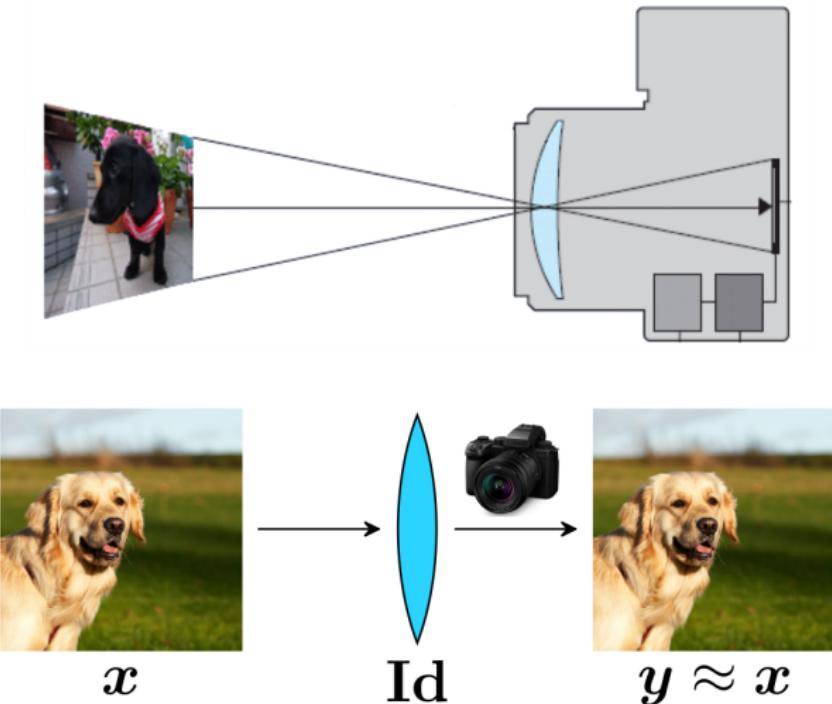
15th May, 2024

Louvain-la-Neuve



Context and notations

Context - Conventional imaging



Context - Computational imaging

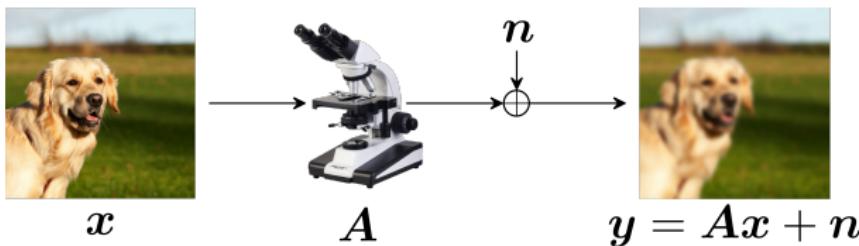
$\mathbf{x} \in \mathbb{R}^N$: object to be imaged.

$\mathbf{y} \in \mathbb{R}^M$: measurements.

$\mathbf{A} \in \mathbb{R}^{M \times N}$: forward operator containing the physics (generally linear).

→ \mathbf{A} can be partial, ill-conditioned,...

Forward problem: generate \mathbf{y} from \mathbf{x} .



Inverse problem: recover \mathbf{x} from the observations \mathbf{y} .

Context - Computational imaging

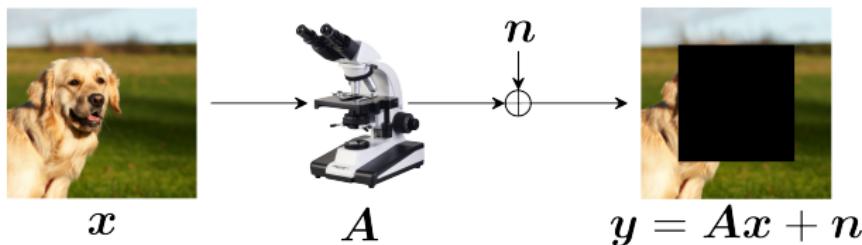
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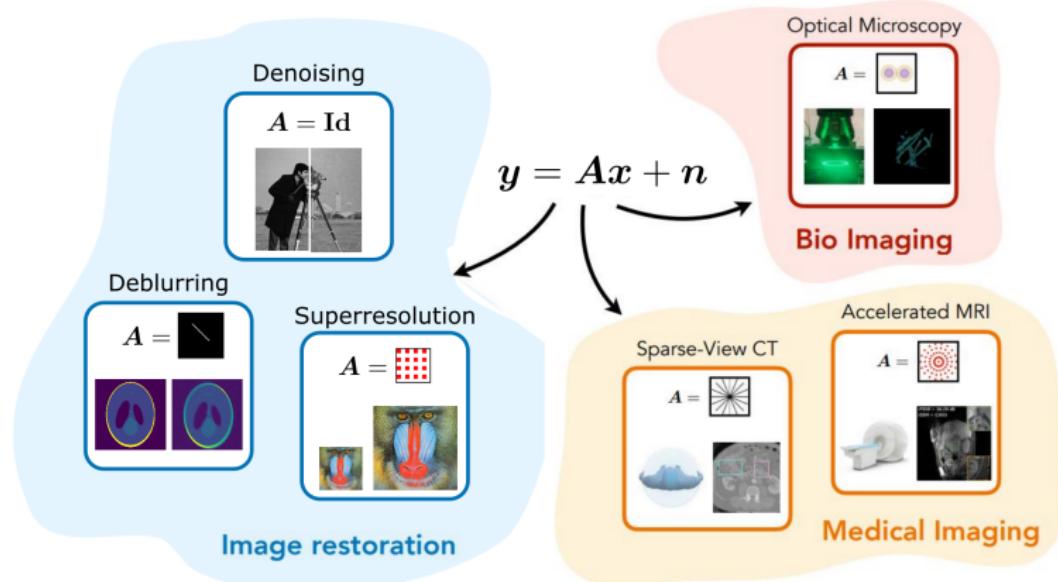
Forward problem: generate \mathbf{y} from \mathbf{x} .



Inverse problem: recover \mathbf{x} from the observations \mathbf{y} .

Context - Computational imaging

Many computational imaging problems
can be formulated as inverse problems



1

¹inspired from Yu Sun

Context - MultiCore Fiber Lensless Imaging (MCF-LI)



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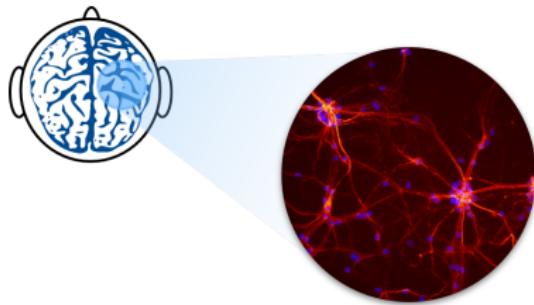
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Context - MultiCore Fiber Lensless Imaging (MCF-LI)

Motivation:

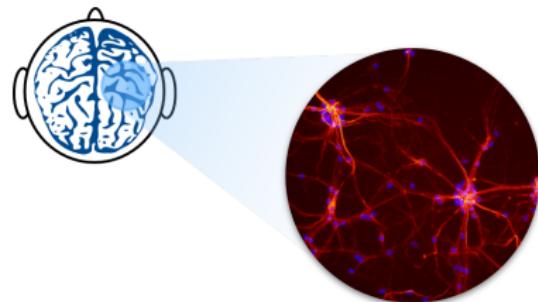
- ▶ Deep brain imaging.
- ▶ Limited invasiveness.



Context - MultiCore Fiber Lensless Imaging (MCF-LI)

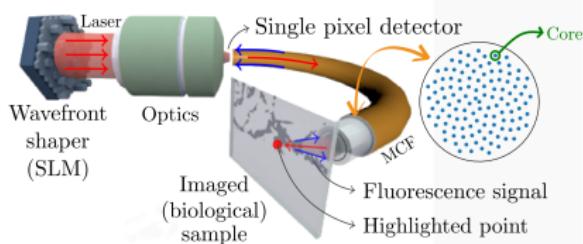
Motivation:

- ▶ Deep brain imaging.
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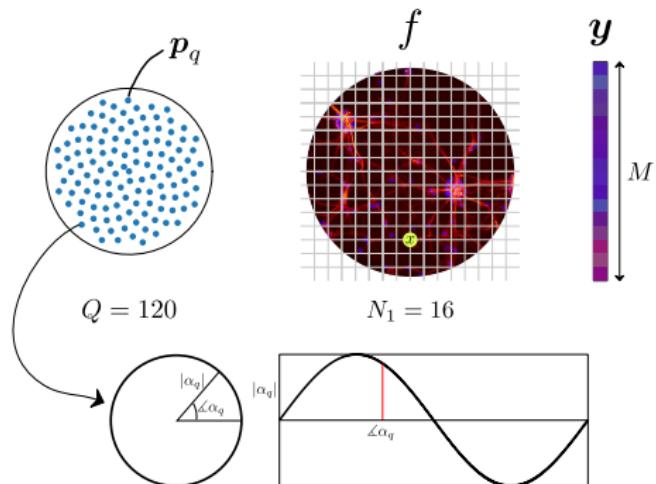
Challenges:

- ▶ Fluorescence imaging.
- ▶ Single-pixel → limited view.
- ▶ Small intensity.



Notations

p_q	Position of core q
Q	Number of cores
$\alpha \in \mathbb{C}^Q$	Cores complex amplitudes (tunable!)
$x \in \mathbb{R}^2$	2-D object space
$f(x)$	Object to be imaged
$N = N_1 \times N_1$	Image resolution
M	Number of measurements
$y \in \mathbb{R}_+^M$	Measurement vector



Outline

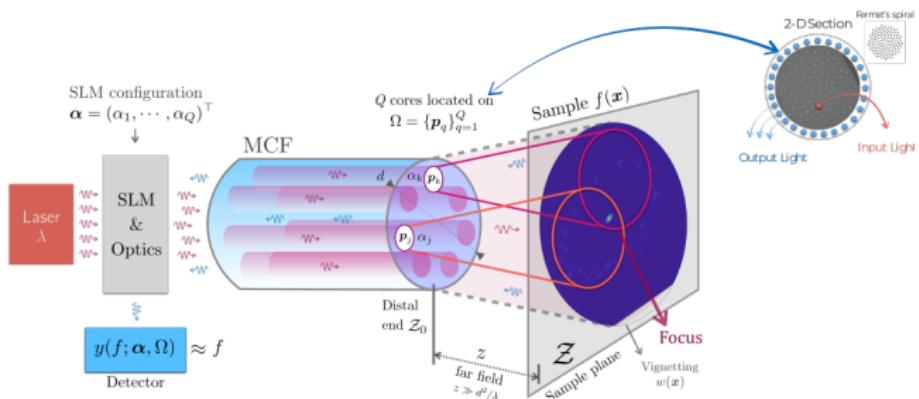
1. Context and notations
2. Existing models: Raster Scanning (RS) and Speckle Illuminations (SI)
3. MCF Interferometric Imaging

Existing models: Raster Scanning (RS) and Speckle Illuminations (SI)

Outline

1. Context and notations
2. Existing models: Raster Scanning (RS) and Speckle Illuminations (SI)
 - 2.1 Raster scanning
 - 2.2 Speckle illumination
3. MCF Interferometric Imaging

Raster scanning (RS) mode

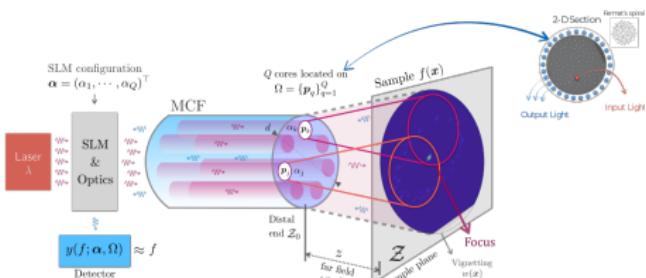


The diagram shows the mathematical representation of the reconstruction process:

$$x * \varphi = y$$

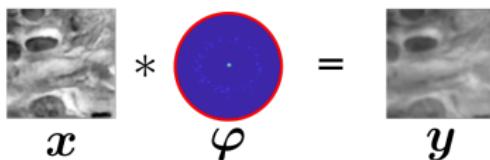
RS mode

Forward model: $\mathbf{y} = \varphi * \mathbf{x}$.
 → Deconvolution problem!



Drawbacks:

- ▶ $M = N$.
- ▶ φ spatially varying.



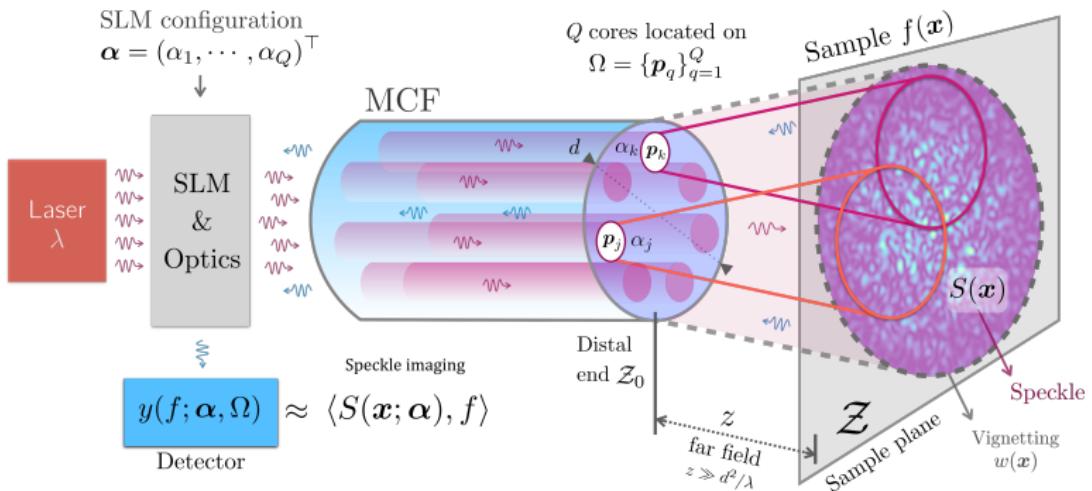
Outline

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Speckle illumination



Steph. Guérit



Classical Compressive Sensing

$$y_m = \mathbf{a}_m^\top \mathbf{x}$$
$$y_m = \mathbf{a}_m^\top \mathbf{x} = \langle \mathbf{a}_m, \mathbf{x} \rangle$$

Classical Compressive Sensing

$$\begin{matrix} \mathbf{y} \\ M \end{matrix} = \boxed{\mathbf{A}}_{M \times N} \begin{matrix} \mathbf{x} \\ N \end{matrix}$$

The diagram illustrates the mathematical model of compressive sensing. On the left, a vertical vector \mathbf{y} of size M is shown as a stack of colored blocks. An equals sign follows. In the center, a matrix \mathbf{A} of size $M \times N$ is depicted as a grid of colored blocks. A dashed rectangular box encloses the matrix \mathbf{A} . To the right of the matrix, a vertical vector \mathbf{x} of size N is shown as a stack of colored blocks, with ellipses indicating intermediate entries.

Condition: a_{mn} are iid random variables (e.g., $a_{mn} \underset{\text{i.i.d.}}{\sim} \mathcal{N}(0, 1)$).

Speckle illumination: model

The m -th single pixel observation is the integration of the m -th speckle pattern \mathbf{s}_m illuminating the sample \mathbf{f} :

$$y_m = \mathbf{s}_m^\top \mathbf{f} + n_m.$$



Classical compressive sensing model (Guerit et al.)

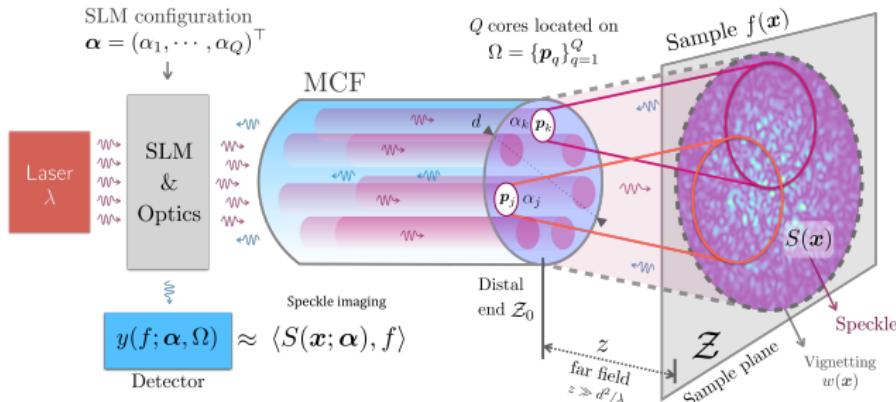
$$\mathbf{y} = \mathbf{S}\mathbf{f} + \mathbf{n}$$

$$\hat{\mathbf{f}} = \arg \min_{\mathbf{f}} \frac{1}{2} \|\mathbf{y} - \mathbf{S}\mathbf{f}\|_2^2 + \mathcal{R}(\mathbf{f})$$

Compressive imaging \Rightarrow number of observations $M \ll N$ image resolution.

Assumption: all coefficients in \mathbf{S} are i.i.d. random variables.

A closer look to sensing model



Generating a N pixels speckle from only Q random coefficients $\boldsymbol{\alpha} = (\alpha_1, \dots, \alpha_Q) \dots$

Why would this behave as a random gaussian waveform?

MCF Interferometric Imaging

Overview

Mathematical modeling



SLM configuration
 $\alpha = (\alpha_1, \dots, \alpha_Q)^\top$



$$y(f; \alpha, \Omega) \approx \alpha^* \mathcal{I}[w f] \alpha$$

Detector

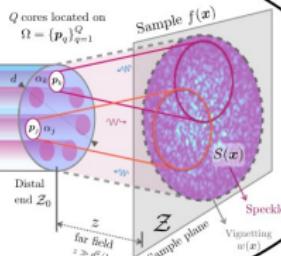
Low structure



Inverse problem & optimisation



Theoretical guarantees



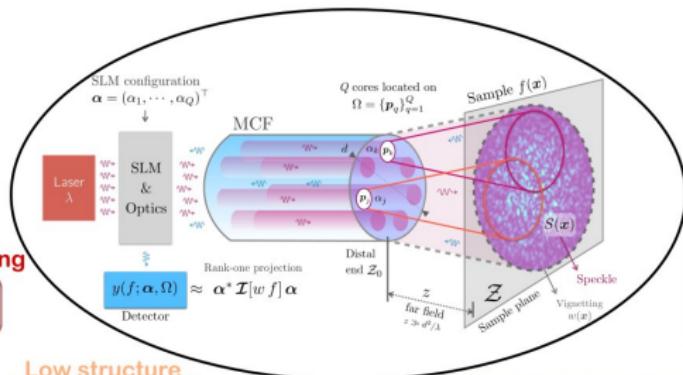
Proof of concept



Mathematical modeling

Mathematical modeling

$$y_m = g(f; \boldsymbol{\alpha}_m) ?$$



Low structure

?

Inverse problem
& optimisation

?

Theoretical guarantees

?

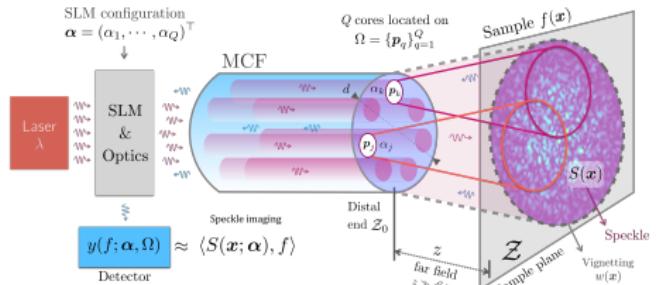
Proof of concept

?

Interferometric imaging

Classical compressive sensing model

$$y_{\alpha} = \int_{\mathbb{R}^2} S_{\alpha}(\mathbf{x}) f(\mathbf{x}) d\mathbf{x} = \langle S_{\alpha}, f \rangle$$



Speckles are interferences (Under far-field approximation)

$$E_q(\mathbf{x}) = \alpha_q \sqrt{w(\mathbf{x})} e^{\frac{2\pi i}{\lambda z} \mathbf{p}_q^\top \mathbf{x}}, \quad w(\mathbf{x}) = \frac{|\hat{E}_0(\frac{\mathbf{x}}{\lambda z})|^2}{(\lambda z)^2} \quad (\text{Rayleigh-Sommerfeld})$$

$$S(\mathbf{x}; \alpha) \propto w(\mathbf{x}) \left| \sum_{q=1}^Q \alpha_q e^{\frac{2\pi i}{\lambda z} \mathbf{p}_q^\top \mathbf{x}} \right|^2 = \frac{w(\mathbf{x})}{\text{Field of view}} \sum_{j, k=1}^Q \alpha_j \alpha_k^* e^{\frac{2\pi i}{\lambda z} (\mathbf{p}_j - \mathbf{p}_k)^\top \mathbf{x}}$$

Hence (noiseless)

$$\begin{aligned} y_{\alpha} &= \sum_{j, k=1}^Q \alpha_j \alpha_k^* \left[\int_{\mathbb{R}^2} e^{\frac{2\pi i}{\lambda z} (\mathbf{p}_j - \mathbf{p}_k)^\top \mathbf{x}} w(\mathbf{x}) f(\mathbf{x}) d\mathbf{x} \right] \\ &= \alpha^* \mathcal{I}_{\Omega} [wf] \alpha = \langle \alpha \alpha^*, \mathcal{I}_{\Omega} [wf] \rangle \end{aligned}$$

Interferometric imaging

Writing $f^\circ := wf$ we have

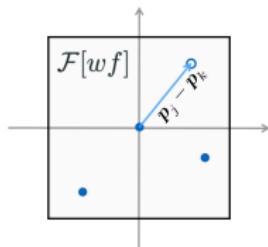
$$y_\alpha = \alpha^* \mathcal{I}_\Omega[f^\circ] \alpha$$

with the interferometric matrix $\mathcal{I}_\Omega[f^\circ] \in \mathbb{C}^{Q \times Q}$ s.t.

$$(\mathcal{I}_\Omega[f^\circ])_{j,k} := \int_{\mathbb{R}^2} e^{\frac{2\pi i}{\lambda z} (\mathbf{p}_j - \mathbf{p}_k)^\top} f^\circ(\mathbf{x}) d\mathbf{x}$$

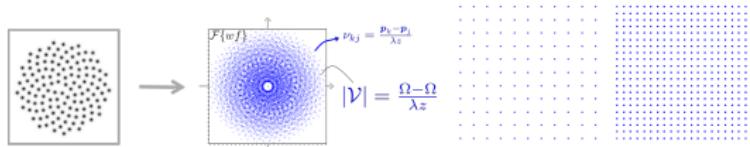
Observation: denser Fourier sampling if

$$|\{\mathbf{p}_j - \mathbf{p}_k : \forall 1 \leq j, k \leq Q\}| \simeq Q^2$$



Fourier plane

- ▶ Lattices are bad core arrangements
- ▶ Fermat's spiral is not bad



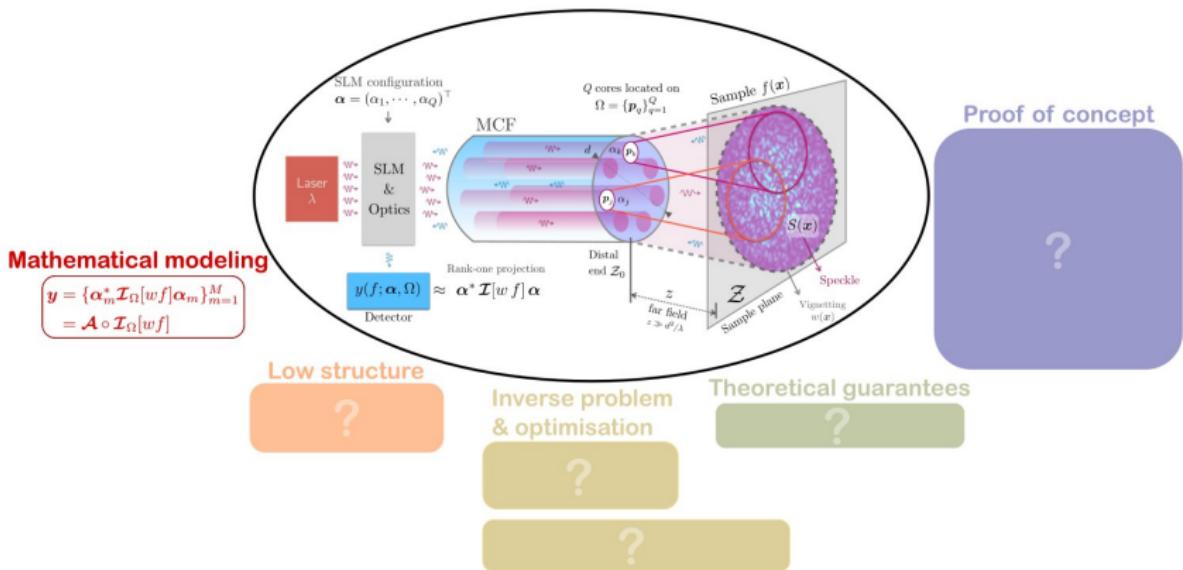
$$\begin{aligned}\mathbf{y} &= \{\boldsymbol{\alpha}_m^* \mathcal{I}_\Omega[f^\circ] \boldsymbol{\alpha}_m\}_{m=1}^M \\ &= \mathcal{A} \circ \mathcal{I}_\Omega[f^\circ]\end{aligned}$$

Two-component sensing!

\mathcal{A} : Symmetric rank-one projections of a matrix.

\mathcal{I}_Ω : Partial Fourier sensing with replacement.

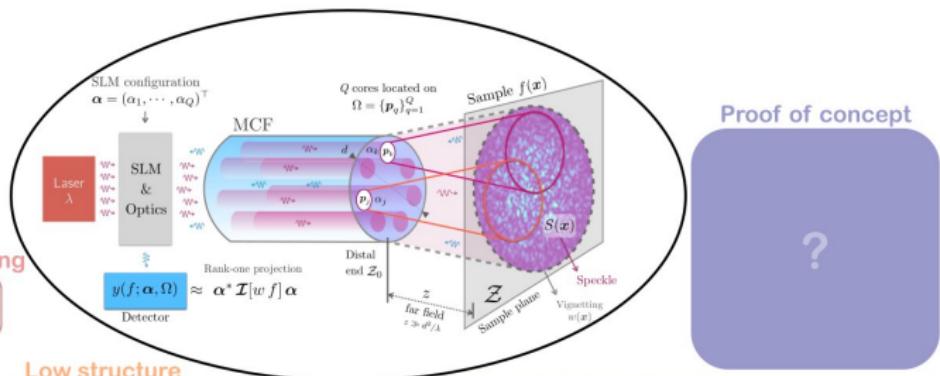
Mathematical model



Inverse problem & optimisation

Mathematical modeling

$$\begin{aligned} \mathbf{y} &= \{\alpha_m^* \mathcal{I}_\Omega[w f] \alpha_m\}_{m=1}^M \\ &= \mathcal{A} \circ \mathcal{I}_\Omega[w f] \end{aligned}$$



Low structure



hermitian
constant diag
low-rank?
low-dim?

Inverse problem & optimisation



Theoretical guarantees

Single-step strategy

Basis Pursuit DeNoising in ℓ_1 -norm (BPDN $_{\ell_1}$)

How to get a \hat{f} from $\mathbf{y} = \mathcal{A} \circ \mathcal{I}_{\Omega}[f^{\circ}]$?

Discretise $f^{\circ} \rightarrow \mathbf{f} \in \mathbb{R}^{N_1 \times N_1}$

The interferometric matrix becomes

$$\mathcal{I}_{\Omega}[f^{\circ}] \approx \mathcal{T}\mathbf{F}\mathbf{f}$$

Let us rewrite

$$\mathcal{B} := \mathcal{A} \circ \mathcal{I}_{\Omega} \text{ s.t. } \mathbf{y} = \mathcal{B}\mathbf{f}$$

Solve

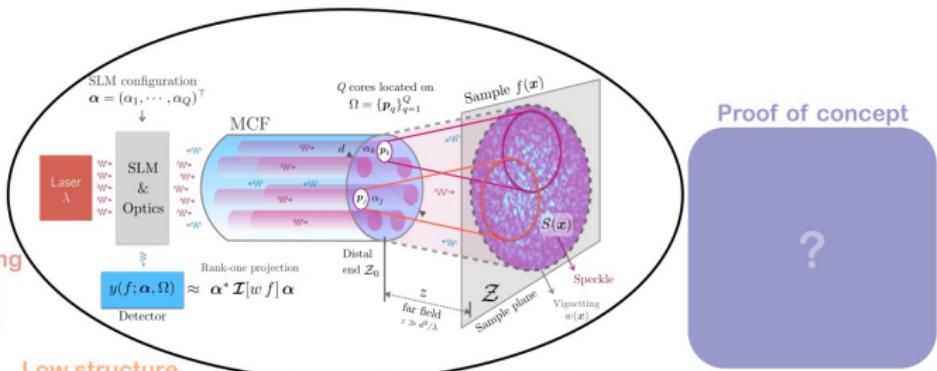
$$\hat{\mathbf{f}} = \arg \min_{\mathbf{u}} \|\mathbf{u}\|_1 \quad \text{s.t. } \|\mathbf{y} - \mathcal{B}\mathbf{u}\|_1 \leq \epsilon \quad (\text{BPDN}_{\ell_1})$$

Here we leverage low structure directly on f° !

Inverse problem & optimisation

Mathematical modeling

$$\begin{aligned} \mathbf{y} &= \{\alpha_m^* \mathcal{I}_\Omega[w f] \alpha_m\}_{m=1}^M \\ &= \mathcal{A} \circ \mathcal{I}_\Omega[w f] \end{aligned}$$



Low structure



hermitian
constant diag
low-rank?
low-dim?

Inverse problem & optimisation

Two-step

1. $\mathbf{y} \rightarrow \mathcal{I}_\Omega[f^*]$
2. $\mathcal{I}_\Omega[f^*] \rightarrow f^*$

Single-step

$$\hat{f} \in \arg \min_u \|u\|_1 \text{ s.t. } \|\mathbf{y} - \mathcal{A} \circ \mathcal{I}_\Omega[u]\|_1 \leq \epsilon$$

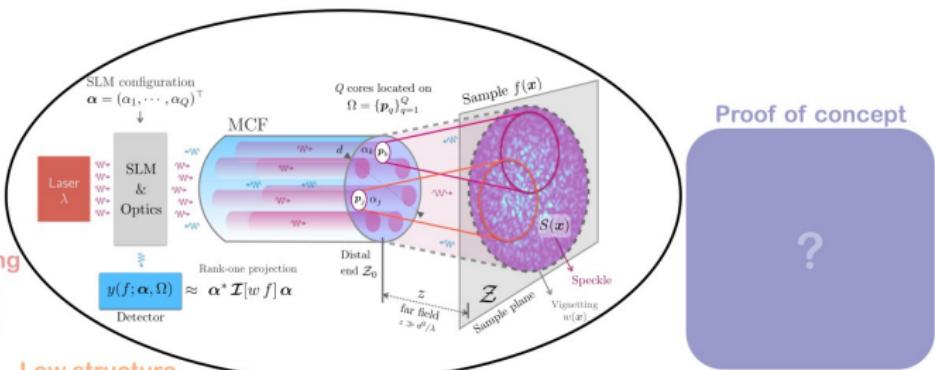
Theoretical guarantees



Recovery guarantees

Mathematical modeling

$$\begin{aligned} \mathbf{y} &= \{\alpha_m^* \mathcal{I}_\Omega[w f] \alpha_m\}_{m=1}^M \\ &= \mathcal{A} \circ \mathcal{I}_\Omega[w f] \end{aligned}$$



Low structure



hermitian
constant diag
low-rank?
low-dim?

Inverse problem & optimisation

Two-step

1. $\mathbf{y} \rightarrow \mathcal{X}_\Omega[f^*]$
2. $\mathcal{X}_\Omega[f^*] \rightarrow f^*$

Single-step

$$f \in \arg \min_u \|u\|_1 \text{ s.t. } \|\mathbf{y} - \mathcal{A} \circ \mathcal{I}_\Omega[u]\|_1 \leq \epsilon$$

Theoretical guarantees



Objective

Show

$$\hat{\mathbf{f}} \in \arg \min_{\mathbf{u}} \|\mathbf{u}\|_1 \quad \text{s.t. } \|\mathbf{y} - \mathcal{A}(\mathcal{I}_{\Omega}[\mathbf{u}])\|_1 \leq \epsilon \quad (\text{BPDN}_{\ell_1})$$

satisfies

$$\|\mathbf{f} - \hat{\mathbf{f}}\|_2 \leq C \frac{\|\mathbf{f} - \mathbf{f}_K\|_1}{\sqrt{K}} + D \frac{\epsilon}{m}.$$

Prove the RIP- ℓ_2/ℓ_1

Proposition

If

$$M \geq CK \log \left(\frac{12eN}{K} \right), \quad Q(Q-1) \geq 4Kp \log(N, K, \delta),$$

the operator $\mathcal{A} \circ \mathcal{I}_{\Omega}$ satisfies

$$\tilde{A} \|\mathbf{u}\| \leq \frac{1}{M} \|\mathcal{A}(\mathcal{I}_{\Omega}[\mathbf{u}])\|_1 \leq \tilde{B} \|\mathbf{u}\|$$

$\forall \mathbf{u} \in \Sigma_K$ with probability exceeding $1 - C \exp(-cM)$.

Recovery guarantees - Stable and robust solution

Objective

Show

$$\hat{\mathbf{f}} \in \arg \min_{\mathbf{u}} \|\mathbf{u}\|_1 \quad \text{s.t. } \|\mathbf{y} - \mathcal{A}(\mathcal{I}_{\Omega}[\mathbf{u}])\|_1 \leq \epsilon \quad (\text{BPDN}_{\ell_1})$$

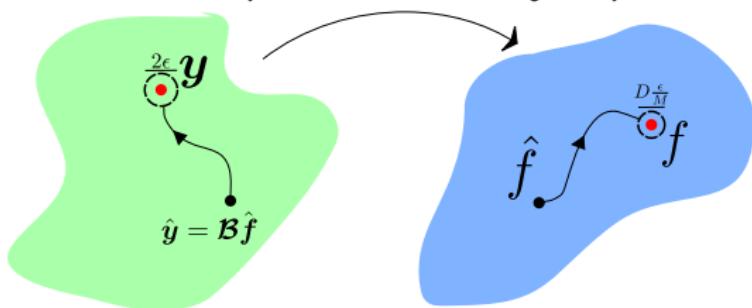
satisfies

$$\|\mathbf{f} - \hat{\mathbf{f}}\|_2 \leq C \frac{\|\mathbf{f} - \mathbf{f}_K\|_1}{\sqrt{K}} + D \frac{\epsilon}{m}.$$

Prove the RIP- ℓ_2/ℓ_1

$$\tilde{A}\|\mathbf{u}\| \leq \frac{1}{M}\|\mathcal{A}(\mathcal{I}_{\Omega}[\mathbf{u}])\|_1 \leq \tilde{B}\|\mathbf{u}\|$$

Measurement space Object space



Recovery Guarantees - Combine RIPs

Objective

Show

$$\hat{\mathbf{f}} \in \arg \min_{\mathbf{u}} \|\mathbf{u}\|_1 \quad \text{s.t. } \|\mathbf{y} - \mathcal{A}(\mathcal{I}_\Omega[\mathbf{u}])\|_1 \leq \epsilon \quad (\text{BPDN}_{\ell_1})$$

satisfies

$$\|\mathbf{f} - \hat{\mathbf{f}}\|_2 \leq C \frac{\|\mathbf{f} - \mathbf{f}_K\|_1}{\sqrt{K}} + D \frac{\epsilon}{m}.$$

- ▶ Assume RIP- ℓ_2/ℓ_2 for visibility sampling

$$(1 - \delta) \|\mathbf{u}\|^2 \leq \|\mathcal{I}_\Omega[\mathbf{u}]\|_F^2 \leq (1 + \delta) \|\mathbf{u}\|^2, \quad \forall \mathbf{u} \in \Sigma_K.$$

- ▶ Prove ℓ_2/ℓ_1 -concentration for SROPs

$$A \|\mathcal{I}_\Omega\|_F \leq \frac{1}{M} \|\mathcal{A}(\mathcal{I}_\Omega)\|_1 \leq B \|\mathcal{I}_\Omega\|_F$$

with very high probability.

- ▶ Combine the two and use union bound to get RIP- ℓ_2/ℓ_1

$$\tilde{A} \|\mathbf{u}\| \leq \frac{1}{M} \|\mathcal{A}(\mathcal{I}_\Omega[\mathbf{u}])\|_1 \leq \tilde{B} \|\mathbf{u}\|$$

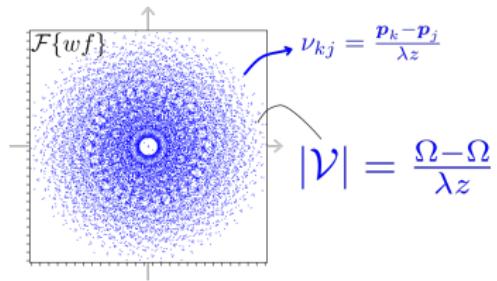
Assumption (inspired by partial Fourier sensing in CS²)

$$(1 - \delta)\|\mathbf{u}\|^2 \leq \|\mathcal{I}_\Omega[\mathbf{u}]\|_F^2 \leq (1 + \delta)\|\mathbf{u}\|^2$$

with the condition

$$|\mathcal{V}_0| = Q(Q - 1) \geq \delta^{-2} K \log(N, K, \delta)$$

We need randomness in the sampling
 But deterministic visibility set...
 Hopefully, we have good reasons think this
 assumption is not too bad!



²E. J. Candès, J. K. Romberg, and T. Tao, “Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information,” IEEE Transactions on Information Theory, vol. 52, no. 2, pp. 489–509, 2006.

Recovery guarantees - Proving the RIP- ℓ_2/ℓ_1

$$A\|\mathcal{I}_\Omega\|_F \leq \frac{1}{M}\|\mathcal{A}(\mathcal{I}_\Omega)\|_1 \leq B\|\mathcal{I}_\Omega\|_F$$

If $M > CK \log\left(\frac{12eN}{K}\right)$ and \mathcal{A} satisfies

$$\mathbb{P}\left[\left|\frac{1}{\sqrt{M}}\|\mathcal{A}(\mathcal{I})\|_1 - \|\mathcal{I}\|_F\right| > t\|\mathcal{I}\|_F\right] \leq Ce^{-cM} \quad (1)$$

$\Rightarrow \mathcal{A}$ satisfies RIP- ℓ_2/ℓ_1 w.h.p.

Prove (1) in two-steps

Recovery guarantees - Proving the RIP- ℓ_2/ℓ_1

If $M > CK \log\left(\frac{12eN}{K}\right)$ and \mathcal{A} satisfies

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Prove (1) in two-steps

$$1. \mathbb{P} [|\|\mathcal{A}(\mathcal{I})\|_1 - \mathbb{E} \|\mathcal{A}(\mathcal{I})\|_1| > t] \leq 2 \exp \left(-cM \min \left(\frac{t^2}{4\kappa^2}, \frac{t}{2\kappa} \right) \right)$$

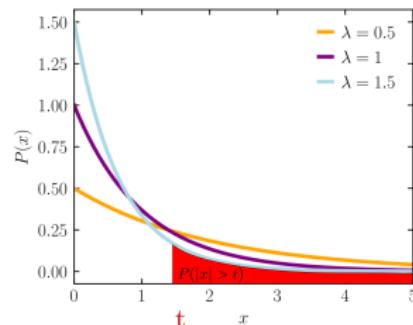
$$\|\mathcal{A}(\mathcal{I})\|_1 = \sum_{m=1}^M |\boldsymbol{\alpha}_m^* \mathcal{I} \boldsymbol{\alpha}_m| = \sum_{m=1}^M |\xi_m|$$

$$\|\mathcal{A}(\mathcal{I})\|_1 - \mathbb{E} \|\mathcal{A}(\mathcal{I})\|_1 = \sum_{m=1}^M |\xi_m| - \mathbb{E} |\xi_m| = \sum_{m=1}^M |\tilde{\xi}_m|$$

Recall $\boldsymbol{\alpha}$ is a r.v. $\Rightarrow \tilde{\xi}$ is a r.v. too.

$\tilde{\xi}_m$ is **subexponential!** Property of a subexponential r.v.

$$\mathbb{P} [|\tilde{\xi}| > t] \leq 2 \exp \left(-cM \min \left(\frac{t^2}{4\kappa^2}, \frac{t}{2\kappa} \right) \right)$$



Recovery guarantees - Proving the RIP- ℓ_2/ℓ_1

If $M > CK \log\left(\frac{12eN}{K}\right)$ and \mathcal{A} satisfies

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Prove (1) in two-steps

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Recovery guarantees - Proving the RIP- ℓ_2/ℓ_1

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2. α_m is i.i.d. as the sub-Gaussian r.v.

$$c_\alpha \|\mathcal{I}\|_F \leq \frac{1}{\sqrt{M}} \mathbb{E} \|\mathcal{A}(\mathcal{I})\|_1 \leq \|\mathcal{I}\|_F .$$

Recovery guarantees - Proving the RIP- ℓ_2/ℓ_1

If $M > CK \log\left(\frac{12eN}{K}\right)$ and \mathcal{A} satisfies

$$\mathbb{P}\left[\left|\frac{1}{\sqrt{M}}\|\mathcal{A}(\mathcal{I})\|_1 - \|\mathcal{I}\|_F\right| > t\|\mathcal{I}\|_F\right] \leq Ce^{-cM} \quad (1)$$

$\Rightarrow \mathcal{A}$ satisfies RIP- ℓ_2/ℓ_1 w.h.p.

Prove (1) in two-steps

1. $\mathbb{P}\left[|\|\mathcal{A}(\mathcal{I})\|_1 - \mathbb{E}\|\mathcal{A}(\mathcal{I})\|_1| > t\right] \leq 2\exp\left(-cM \min\left(\frac{t^2}{4\kappa^2}, \frac{t}{2\kappa}\right)\right)$
2. α_m is i.i.d. as the sub-Gaussian r.v.

$$c_\alpha \|\mathcal{I}\|_F \leq \frac{1}{\sqrt{M}} \mathbb{E}\|\mathcal{A}(\mathcal{I})\|_1 \leq \|\mathcal{I}\|_F.$$

$$(1-t)\mathbb{E}\|\mathcal{A}(\mathcal{I})\|_1 \leq \frac{1}{\sqrt{M}}\|\mathcal{A}(\mathcal{I})\|_1 \leq (1+t)\mathbb{E}\|\mathcal{A}(\mathcal{I})\|_1$$

$$(1-t)c_\alpha \|\mathcal{I}\|_F \leq \frac{1}{\sqrt{M}}\|\mathcal{A}(\mathcal{I})\|_1 \leq (1+t)\|\mathcal{I}\|_F$$

Objective

Show

$$\hat{\mathbf{f}} \in \arg \min_{\mathbf{u}} \|\mathbf{u}\|_1 \quad \text{s.t. } \|\mathbf{y} - \mathcal{A}(\mathcal{I}_\Omega[\mathbf{u}])\|_1 \leq \epsilon \quad (\text{BPDN}_{\ell_1})$$

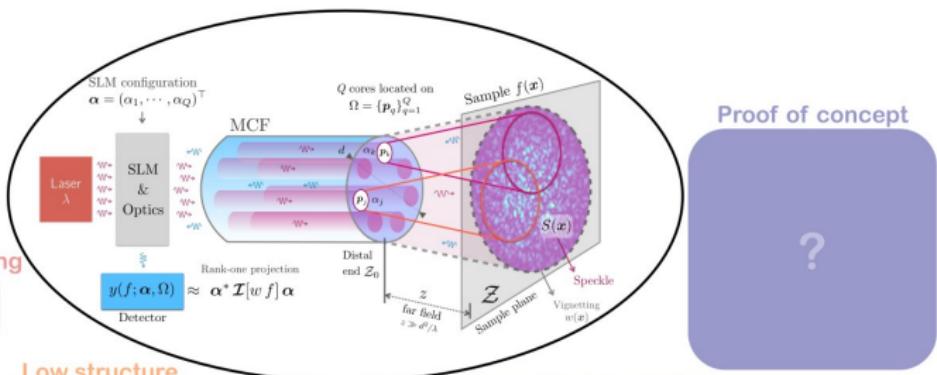
satisfies

$$\|\mathbf{f} - \hat{\mathbf{f}}\|_2 \leq C \frac{\|\mathbf{f} - \mathbf{f}_K\|_1}{\sqrt{K}} + D \frac{\epsilon}{m}.$$

Recovery guarantees

Mathematical modeling

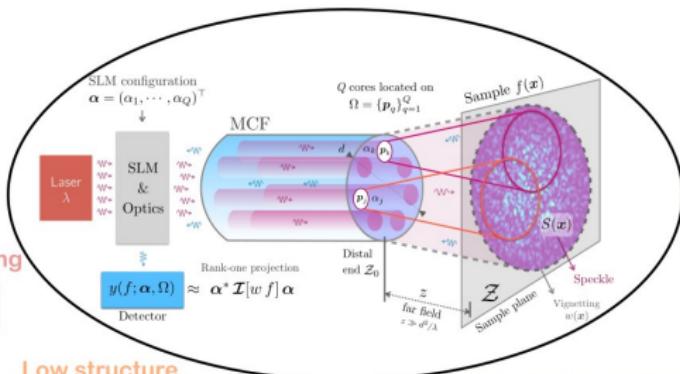
$$\begin{aligned} \mathbf{y} &= \{\alpha_m^* \mathcal{I}_\Omega[w f] \alpha_m\}_{m=1}^M \\ &= \mathcal{A} \circ \mathcal{I}_\Omega[w f] \end{aligned}$$



Proof of concept

Mathematical modeling

$$\begin{aligned} \mathbf{y} &= \{\alpha_m^* \mathcal{I}_\Omega[w f] \alpha_m\}_{m=1}^M \\ &= \mathcal{A} \circ \mathcal{I}_\Omega[w f] \end{aligned}$$



Proof of concept

?

Low structure



hermitian
constant diag
low-rank?
low-dim?

Inverse problem & optimisation

Two-step

1. $\mathbf{y} \rightarrow \mathcal{I}_\Omega[f^*]$
2. $\mathcal{I}_\Omega[f^*] \rightarrow f^*$

Single-step

$$\hat{f} \in \arg \min_u \|u\|_1 \text{ s.t. } \|\mathbf{y} - \mathcal{A} \circ \mathcal{I}_\Omega[u]\|_1 \leq \epsilon$$

Theoretical guarantees

$$\left\| \mathbf{f} - \hat{\mathbf{f}} \right\|_2 \leq C \frac{\| \mathbf{f} - f_K \|_1}{\sqrt{K}} + D \frac{\epsilon}{m}$$

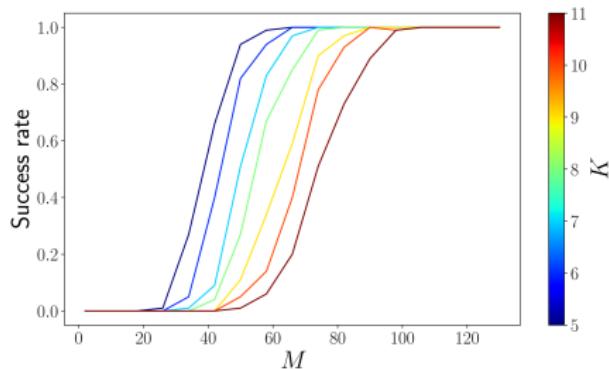
Simulation results

K = sparsity of f , $f \in \Sigma_K$.

$|\mathcal{V}|$ = cardinality of the visibility set in the Fourier space, grows with Q .

M = number of measurements.

$$\hat{\mathbf{f}} = \arg \min_{\mathbf{u}} \|\mathbf{y} - \mathcal{B}\mathbf{u}\|_2 \quad \text{s.t.} \quad \|\mathbf{u}\|_1 \leq K \quad (\text{LASSO})$$



Success if SNR > 40dB.

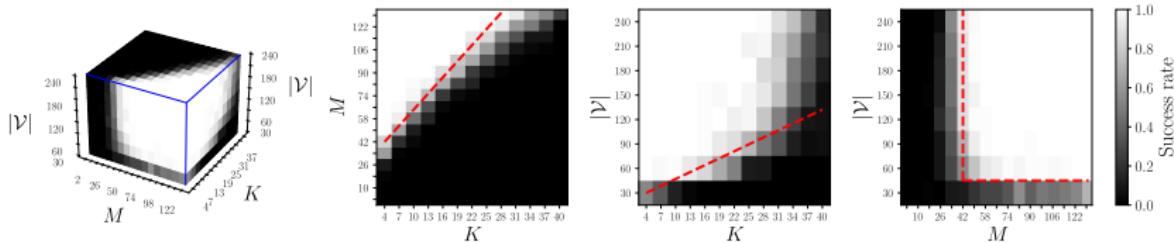
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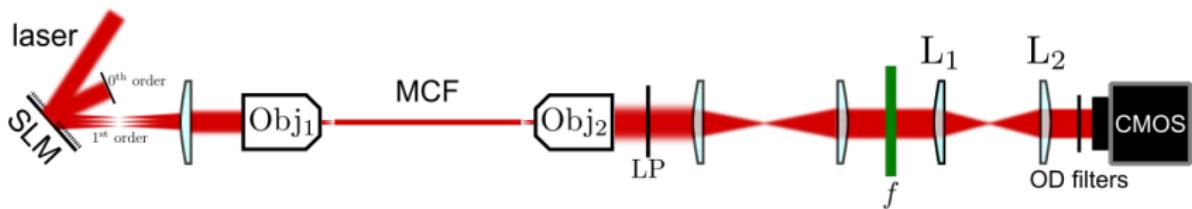
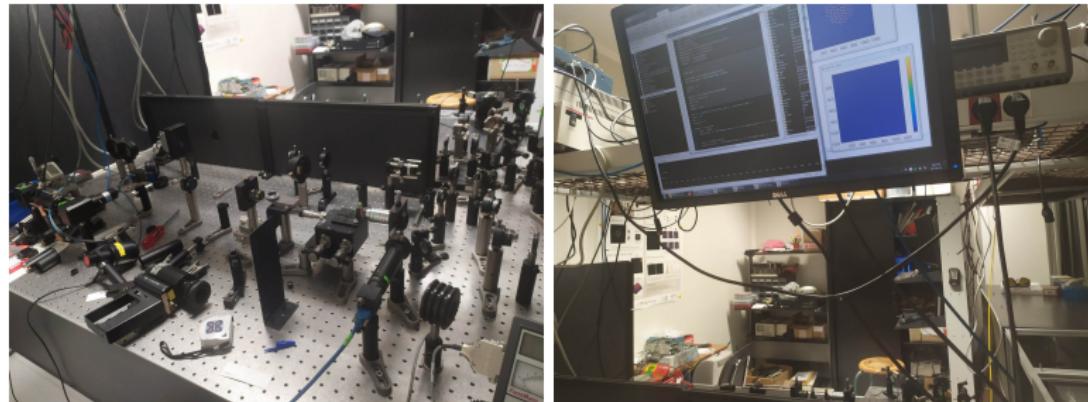


$$M > CK \log \left(\frac{12eN}{K} \right)$$

$$|\mathcal{V}_0| = Q(Q-1) \geq \delta^{-2} K \text{plog}(N, K, \delta)$$

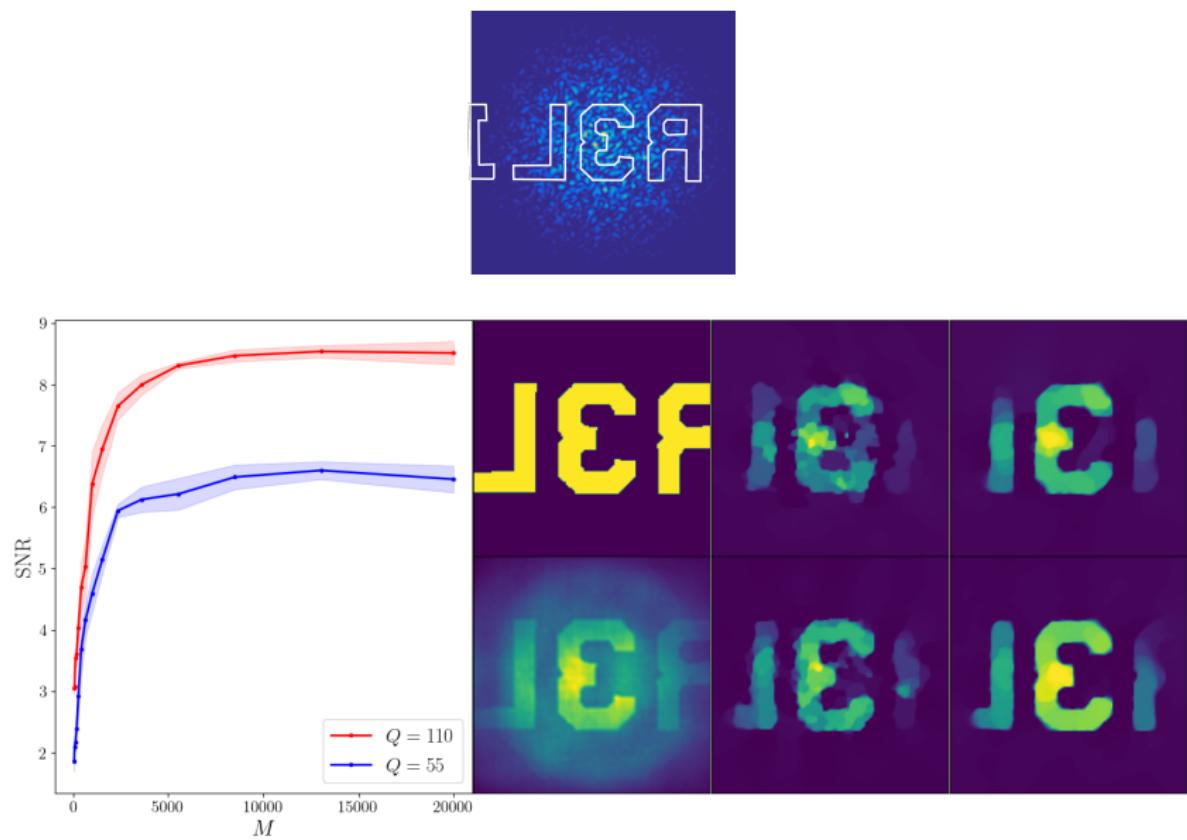
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Experimental results

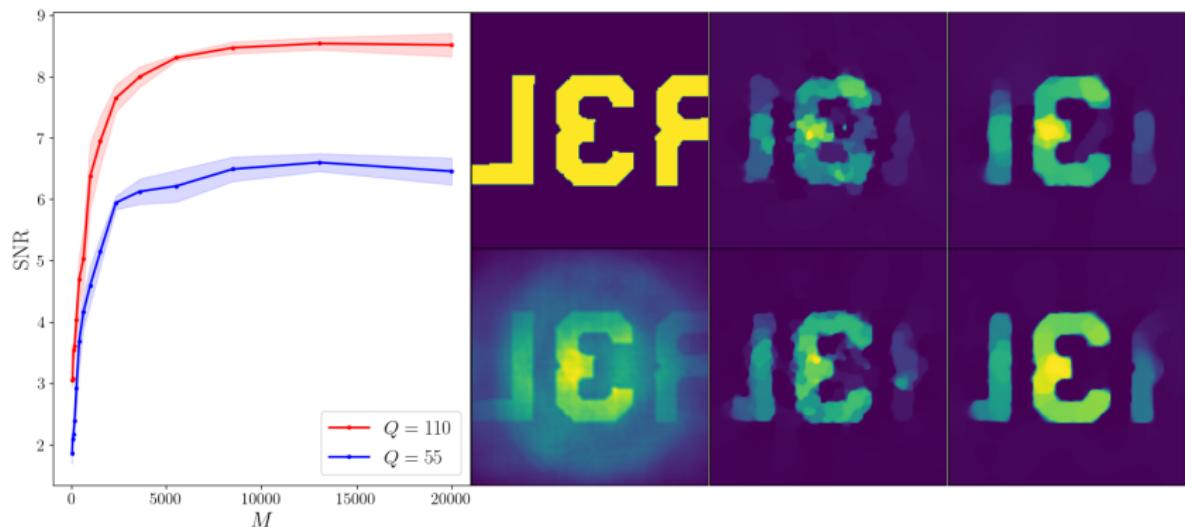


Laser: $\lambda = 1053\text{nm}$. $L_1 : 75\text{mm}$, $L_2 : 100\text{mm}$. MCF diameter: $113\mu\text{m}$. core diameter: $3.2\mu\text{m}$.

Experimental results



Experimental results

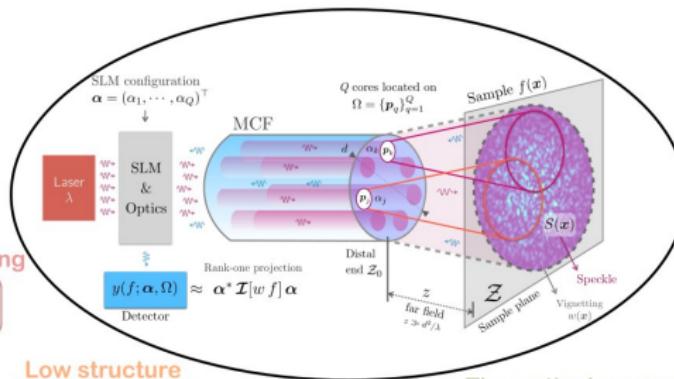


Why such a small SNR?

Proof of concept

Mathematical modeling

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Low structure



hermitian
constant diag
low-rank?
low-dim?

Inverse problem & optimisation

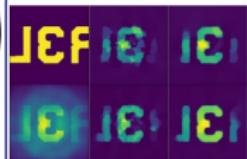
Two-step

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Single-step

$$\hat{f} \in \arg \min_u \|u\|_1 \text{ s.t. } \|\mathbf{y} - \mathcal{A} \circ \mathcal{I}_\Omega[u]\|_1 \leq \epsilon$$

Proof of concept



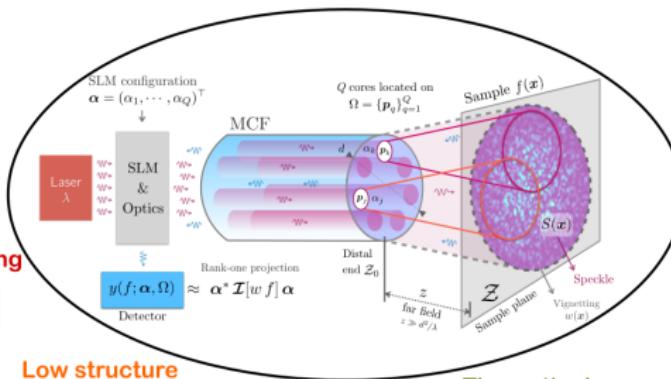
Theoretical guarantees

$$\left\| \mathbf{f} - \hat{\mathbf{f}} \right\|_2 \leq C \frac{\| \mathbf{f} - f_K \|_1}{\sqrt{K}} + D \frac{\epsilon}{m}$$

Proof of concept

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$$\left\| f - \hat{f} \right\|_2 \leq C \frac{\|f - f_K\|_1}{\sqrt{K}} + D \frac{\epsilon}{m}$$

Conclusion

Conclusion

Until now

- ▶ New interferometric model for MCF-LI.
- ▶ Theoretical guarantees.
- ▶ Simulated and experimental results.

Perspectives

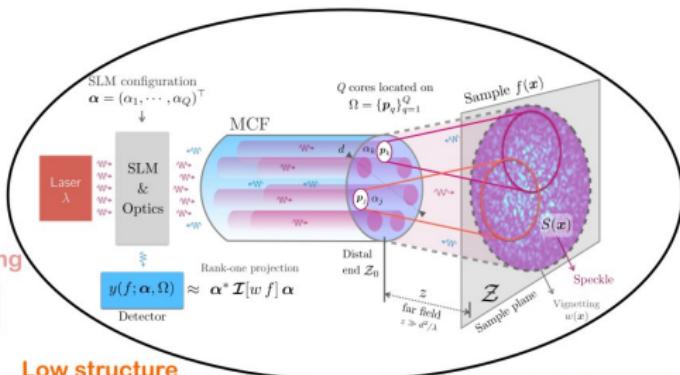
- ▶ Extension to 3D imaging.
- ▶ Experiments in endoscopic conditions.
- ▶ Acceleration of the sensing using mirrors.
- ▶ Manage twisting.

Thank you!

Low structure & complexity

Mathematical modeling

$$\begin{aligned} \mathbf{y} &= \{\alpha_m^* \mathcal{I}_\Omega[w f] \alpha_m\}_{m=1}^M \\ &= \mathcal{A} \circ \mathcal{I}_\Omega[w f] \end{aligned}$$



Low structure

?

Inverse problem
& optimisation

?

Theoretical guarantees

?

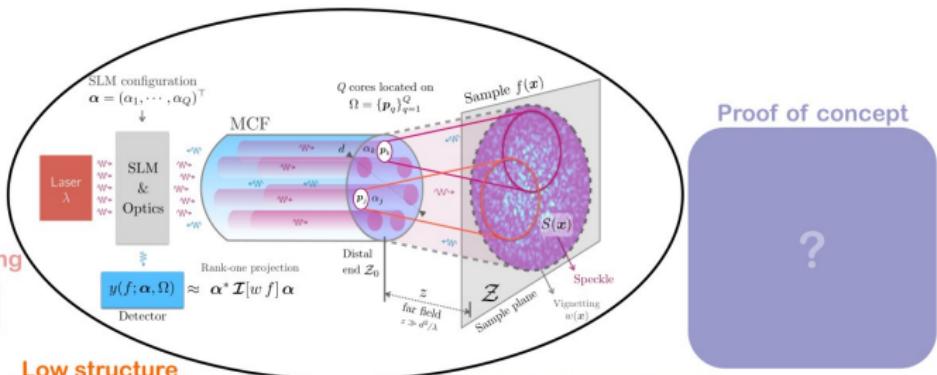
Proof of concept

?

Low structure & complexity

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Low structure



Inverse problem
& optimisation



Theoretical guarantees



Proof of concept



$$(\mathcal{I}_\Omega[f^\circ])_{j,k} := \int_{\mathbb{R}^2} e^{\frac{2\pi i}{\lambda z} (\mathbf{p}_j - \mathbf{p}_k)^\top \mathbf{x}} f^\circ(\mathbf{x}) d\mathbf{x}$$

- ▶ Constant diagonal $(\mathcal{I}_\Omega[f^\circ])_{q,q} = \int_{\mathbb{R}^2} f^\circ(\mathbf{x}) d\mathbf{x} = \langle f^\circ \rangle, \quad \forall q \in [Q]$
- ▶ Hermitian $(\mathcal{I}_\Omega[f^\circ])_{j,k} = (\mathcal{I}_\Omega[f^\circ])_{k,j}^*$

$\Rightarrow Q \times Q$ matrix with only $Q(Q - 1)/2$ degrees of freedom.

Possible structural models on $\mathcal{I}_\Omega[f^\circ]$

Given $\mathcal{I}_\Omega[f^\circ]$

$$(\mathcal{I}_\Omega[f^\circ])_{j,k} := \int_{\mathbb{R}^2} e^{\frac{2\pi i}{\lambda z} (\mathbf{p}_j - \mathbf{p}_k)^\top \mathbf{x}} f^\circ(\mathbf{x}) d\mathbf{x}$$

- If $f^\circ(\mathbf{x}) = \sum_i^K \rho_i \delta(\mathbf{x} - \mathbf{x}_i) \Rightarrow f^\circ \in \Sigma_K$, $\mathcal{I}_\Omega[f^\circ]$ is low-rank

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$$\mathcal{I}_\Omega[f^\circ] = \sum_i^K \rho_i \mathbf{u}(\mathbf{x}_i) \mathbf{u}^*(\mathbf{x}_i), \quad \mathbf{u}(\mathbf{x})_j := e^{i 2\pi \mathbf{p}_j^\top \mathbf{x}}.$$

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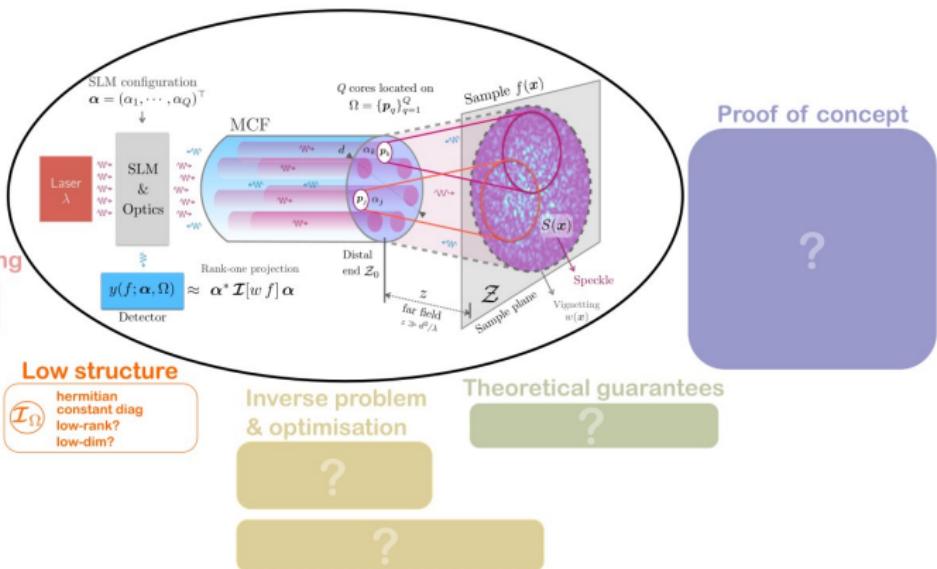
- f° sparse in Ψ (dictionary), $f^\circ(\mathbf{x}) = \sum_i \rho_i \psi_i(\mathbf{x})$
 $\Rightarrow \mathcal{I}_\Omega[f^\circ]$ belongs to a subspace.

$$\mathcal{I}_\Omega[f^\circ] = \frac{1}{Q} \sum_i \rho_i \mathcal{I}_\Omega[\psi_i]$$

Low structure & complexity

Mathematical modeling

$$\begin{aligned} \mathbf{y} &= \{\alpha_m^* \mathcal{I}_\Omega[w f] \alpha_m\}_{m=1}^M \\ &= \mathcal{A} \circ \mathcal{I}_\Omega[w f] \end{aligned}$$



Two-step strategies

Strategy

1. SROPs : $\mathbf{y} \rightarrow \mathcal{I}_\Omega[f^\circ]$
2. Partial Fourier sampling : $\mathcal{I}_\Omega[f^\circ] \rightarrow f^\circ$

1.

- Deterministic schemes

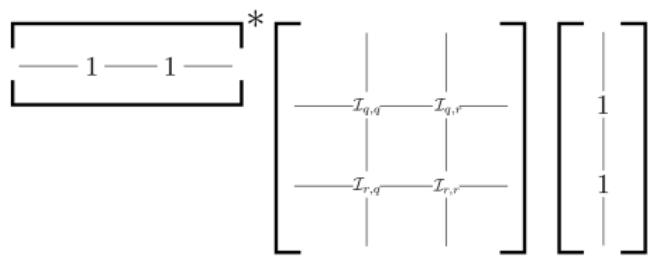
Two-step strategies

- ▶ Deterministic schemes

Two-step strategies

► Deterministic schemes

$$\alpha^* \quad \mathcal{I}_\Omega[f^\circ] \quad \alpha$$

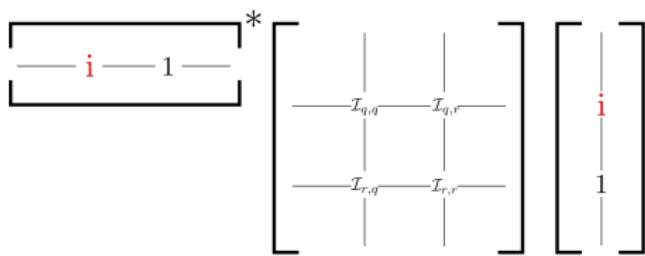


The diagram illustrates a convolution operation. On the left, a 2x2 input matrix with '1' entries is shown. An asterisk (*) indicates it is being multiplied by a 2x2 weight matrix. The weight matrix has diagonal elements labeled $\mathcal{I}_{q,q}$, $\mathcal{I}_{q,r}$, $\mathcal{I}_{r,q}$, and $\mathcal{I}_{r,r}$. The result is a 2x1 output vector with '1' entries.

$$y_1 = \mathcal{I}_{q,q} + \mathcal{I}_{r,r} + 2\Re\{\mathcal{I}_{q,r}\}$$

Two-step strategies

► Deterministic schemes



$$\alpha^* \quad \mathcal{I}_\Omega[f^\circ] \quad \alpha$$

$$y_2 = \mathcal{I}_{q,q} + \mathcal{I}_{r,r} + 2\Im\{\mathcal{I}_{q,r}\}$$

Two-step strategies

► Deterministic schemes

$$y_1 = \mathcal{I}_{q,q} + \mathcal{I}_{r,r} + 2\Re\{\mathcal{I}_{q,r}\}$$

$$y_2 = \mathcal{I}_{q,q} + \mathcal{I}_{r,r} + 2\Im\{\mathcal{I}_{q,r}\}$$

$$\begin{aligned} y_1 + i y_2 &= (1+i)(\mathcal{I}_{q,q} + \mathcal{I}_{r,r}) + 2\mathcal{I}_{q,r} \\ &= 2(1+i)\hat{f}(0) + 2\mathcal{I}_{q,r} \end{aligned}$$

$$\Rightarrow M = Q(Q-1) + 1$$

Two-step strategies

- ▶ Deterministic schemes

- ▶ **Inverse problem**

$f^\circ \in \Sigma_K \Rightarrow \mathcal{I}_\Omega$ is rank- K .

Solve

$$\arg \min_{\mathcal{I}} \|\mathcal{I}\|_* \quad \text{s.t.} \quad \|\mathbf{y} - \mathcal{A}(\mathcal{I})\|_1 \leq \varepsilon$$

Upper bound on the reconstruction error

$$\|\hat{\mathcal{I}} - \mathcal{I}_0\|_F \leq C \frac{\|\mathcal{I}_0 - (\mathcal{I}_0)_K\|_*}{\sqrt{K}} + D \frac{\varepsilon}{M}.$$