Blind Deconvolution in Microscopy

Minh-Hai NGUYEN, Florian SARRON, Paul ESCANDE, Pierre WEISS
IRIT/CBI, Université de Toulouse, France.
minh-hai.nguyen@univ-tlse3.fr https://mh-nguyen712.github.io/

Introduction

Blind Deconvolution — recover a sharp image x and the point-spread-function (PSF) h from a measurement y observed with the degradation $\mathcal{D}$:

$$y = \mathcal{D}(h \star x). \tag{1}$$

We propose a learning method for PSF identification in Blind Deconvolution for Microscopy, building upon the advancements of [1].

Fresnel Diffraction-limited Blurs

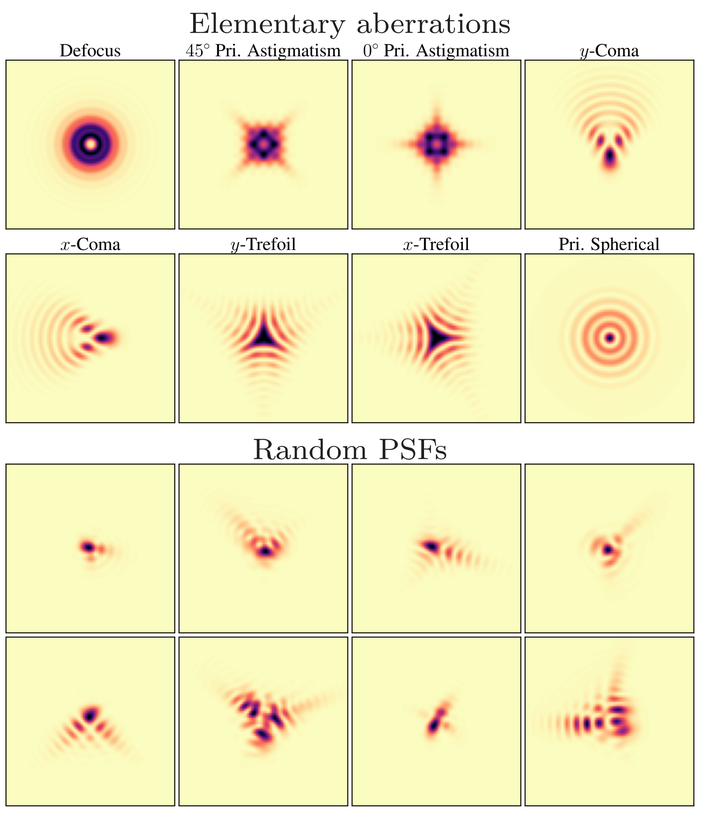
Parameterization. The PSF $h : \mathbb{R}^2 \to \mathbb{R}$ is parameterized by θ as:

$$h(\theta) = \left|\mathcal{F}\left(\exp\left(-i2\pi\phi_\theta\right)\right)\right|^2, \tag{2}$$

where $\mathcal{F}$ is the Fourier transform. The pupil function $\phi_\theta : \mathbb{R}^2 \to \mathbb{R}$ is decomposed as:

$$\phi_\theta = \sum_{k=1}^{K} \theta_k z_k, \quad z_k : \text{ Zernike polynomials.}$$

Implemented in deepinv [2]



Physical parameters.
– Cut-off frequency: $f_{\text{fc}} \in [0.125, 0.25]$ (pupil size, Shannon is at 0.25).
– Max amplitude of $\theta_k \sim \mathcal{U}\left[-\theta_{\max}, \theta_{\max}\right]$ (PSF complexity).

Image Formation Model

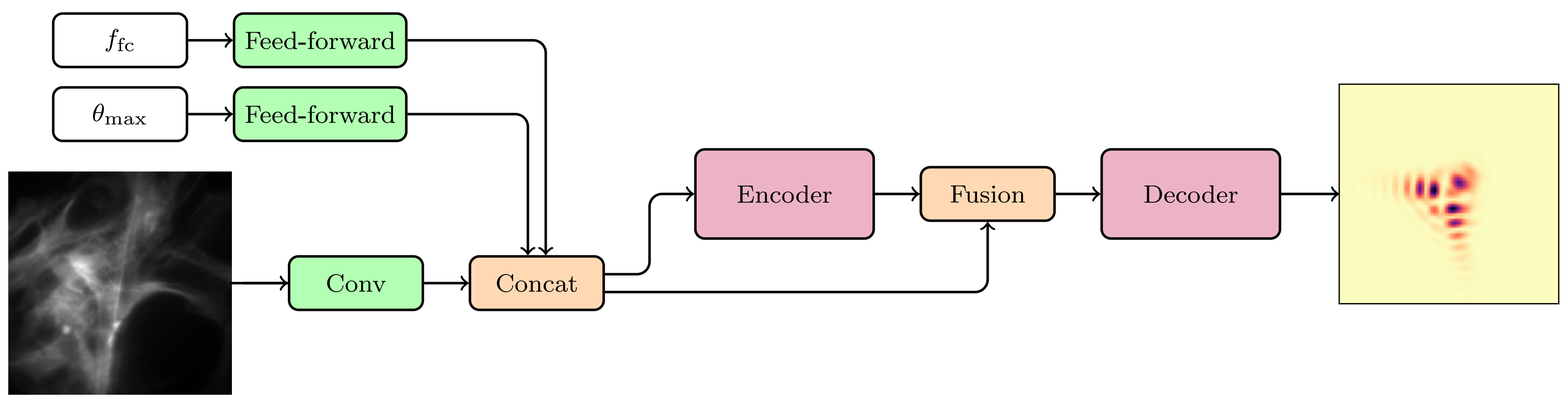
We consider the following degradation:

$$y = S_s Q_q \left(\mathcal{P}_\gamma \left(h(\theta) \star x\right) + \epsilon_\sigma\right), \tag{3}$$

where $\epsilon_\sigma \sim \mathcal{N}(0, \sigma^2 \mathrm{Id})$: white Gaussian noise
$\mathcal{P}_\gamma$: Poisson noise with gain γ
Q_q : quantization at q-bits
S_s : salt-and-pepper noise with prob. s

Identification Neural Network – $N_w(y, f_{\text{fc}}, \theta_{\max})$

Architecture: estimate the PSF at the center of a patch, **conditioned** to the cutoff frequency and the Zernike amplitude.



Synthesize random measurements y following (3): $(\sigma, \gamma, \theta, f_{\text{fc}}, \theta_{\max})$ are **random** following μ, $q = 16-$bits and $s = 10^{-5}$.

Supervised training identification neural network.

$$\min_w \mathbb{E}_{\mu,\boldsymbol{x}}\left[\|\hat{\boldsymbol{h}} - h(\boldsymbol{\theta})\|_1\right] + \lambda \mathbb{E}_{\mu,\boldsymbol{x}}\left[\|\hat{\boldsymbol{h}} \star \boldsymbol{x} - \boldsymbol{y}\|_1\right], \tag{4}$$

where $\hat{\boldsymbol{h}} = N_w\left(\boldsymbol{y}, \boldsymbol{f}_{\text{fc}}, \boldsymbol{\theta}_{\max}\right)$ and $\boldsymbol{y}$ follows (3).

Numerical Results

On synthetized data

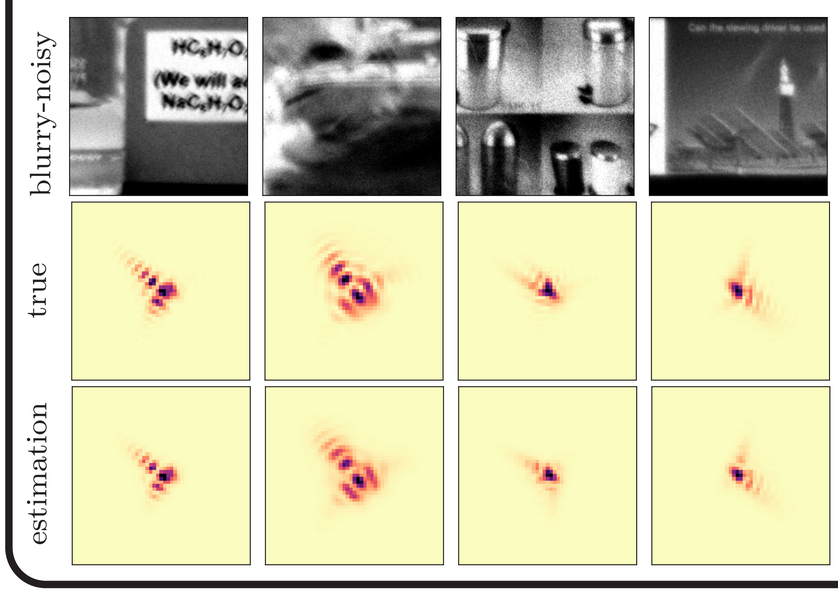
PNSR when the f_{fc} and $\theta_{\max}$ are given

	ImageNet	Flickr2K	Histopathology
$\hat{h}$	52.11 ± 4.63	49.75 ± 4.79	48.67 ± 4.21
$\hat{h} \star x$	37.50 ± 4.92	37.02 ± 5.22	34.50 ± 4.63

PNSR when the f_{fc} and $\theta_{\max}$ are **fixed** to the mean

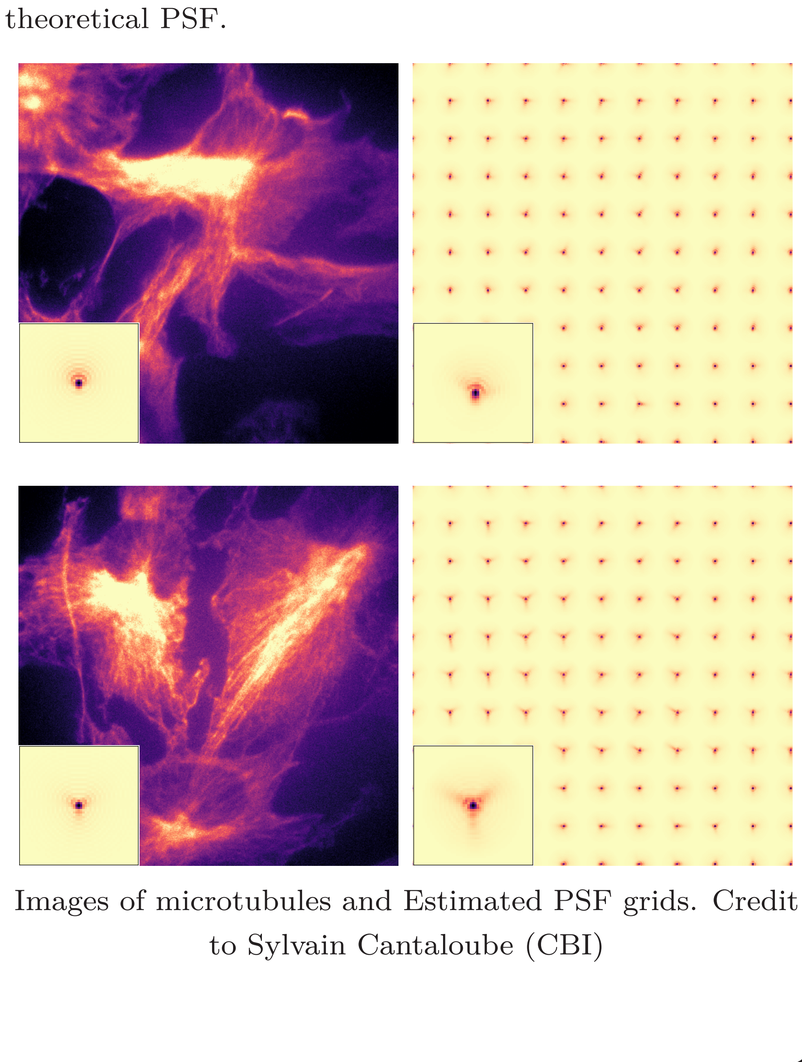
	ImageNet	Flickr2K	Histopathology
$\hat{h}$	47.14 ± 5.16	46.21 ± 4.40	46.06 ± 4.19
$\hat{h} \star x$	35.64 ± 5.56	36.77 ± 5.34	33.71 ± 4.38

Slight performance drop when f_{fc} and $\theta_{\max}$ are unknown.



Real data – Fluorescence TIRF Microscope

With deformable mirror, we can control and estimate the theoretical PSF.



Images of microtubules and Estimated PSF grids. Credit to Sylvain Cantaloube (CBI)

Conclusions and Next steps

- Promissing results on PSF identification, both on synthetic data and real data
- Implementation in Napari (coming soon)
- Consider space-varying blurs (coming soon)
- Training reconstruction network: based on identification network
- Extend to 3D microscopy

References

[1] Valentin Debarnot and Pierre Weiss. Deep-blur: Blind identification and deblurring with convolutional neural networks. *Biological Imaging*, 4:e13, 2024.

[2] DeepInverse. Deepinverse: a pytorch library for imaging with deep learning, 2024.