Training identification network for blind deconvolution in microscopy

PhD Seminar – IRIT

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Contents

Imaging Systems in Microscopy

Basic principles

- Goal: see tiny structures by magnifying the image using **lenses**
- Image quality depends on the optical system, including **resolution** and contrast
- Resolution is **limited** by diffraction—light waves **spread** when passing through a lens

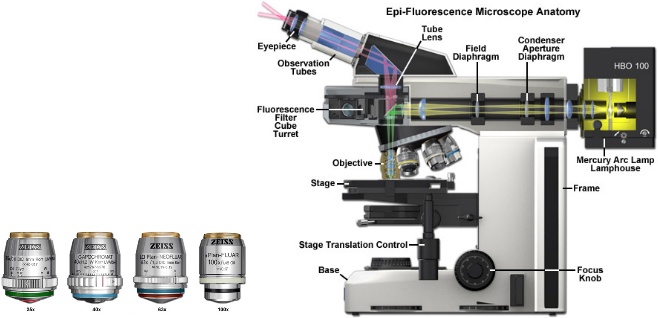

Figure: Objective and Microscope (source: https://zeiss-campus.magnet.fsu.edu/)

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Blurring: optical and physical causes

- Diffraction: even a perfect lens cannot focus light to a single point
- Aberrations: lens imperfections
- Out-of-focus: light from different depths overlaps, causing blur
- Motion Blur: sample movement

$\rightarrow$ Modeled by convolution with a point-spread-function

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Noise

- Photon noise (shot noise)
- Readout noise (camera noise)
- Impulse noise: dead pixels

$\rightarrow$ Modeled by Poisson-Gaussian and salt-and-pepper noise

Example of Microscopy Images

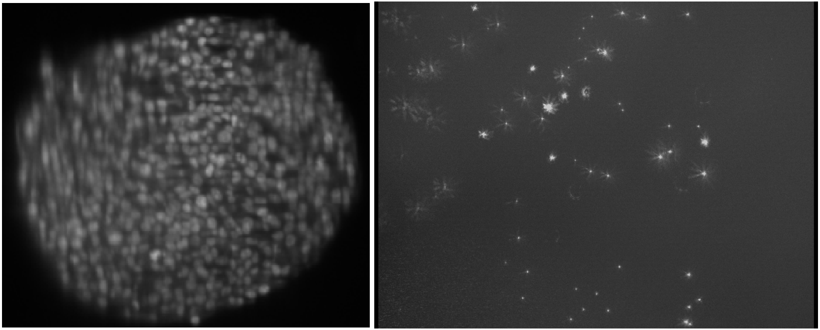

Figure: Source: Microscope database, CBI

Example of Microscopy Images

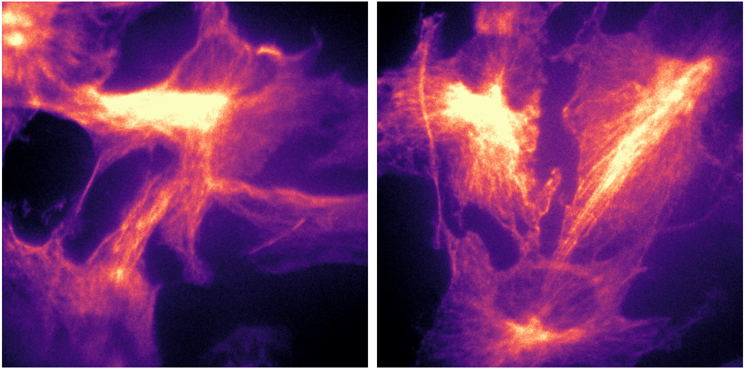

Figure: Credit: Sylvain Cantaloube (Microscopy Platform, CBI)

Microscopy point-spread-function in a nutshell

Point-spread-function (PSF)

Describes the response of a focused optical imaging system to a point source.

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Diffraction barrier

The highest achievable point-to-point resolution that can be obtained with an optical microscope is governed by a fundamental set of physical laws

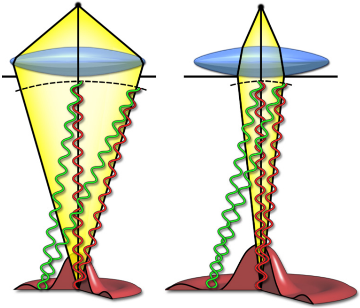


Figure: Resolution limit imposed by wave nature of light (source: https://www.microscopyu.com)

Diffraction-limited blurs

Parameterization

The PSF $h : \mathbb{R}^2 \to \mathbb{R}$ is parameterized by $\theta \in \mathbb{R}^K$ as:

$$h(\theta) = \left|\mathcal{F}\left(\exp\left(-i2\pi\phi_\theta\right)\right)\right|^2, \tag{1}$$

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

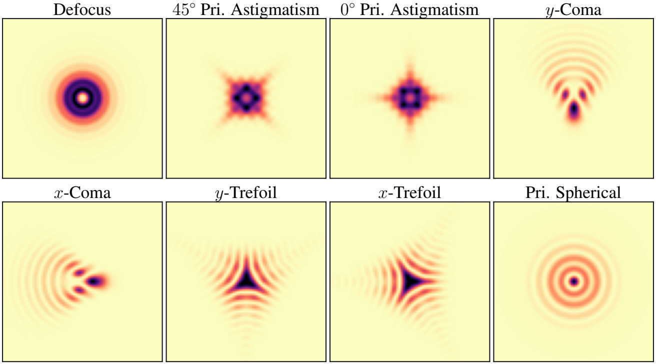
$$\phi_\theta = \sum_{k=1}^{K} \theta_k z_k, \quad z_k : \text{ Zernike polynomials (orthogonal on the unit disk).}$$

Physical parameters

- Cut-off frequency: define the support (in frequency domain) of the Zernike polynomials – $f_{\mathrm{fc}} \in [0.125, 0.25]$ (to respect Shannon).
- Max amplitude of $\theta_k \sim \mathcal{U}\left[-\theta_{\max}, \theta_{\max}\right]$ – define the complexity of the PSF.

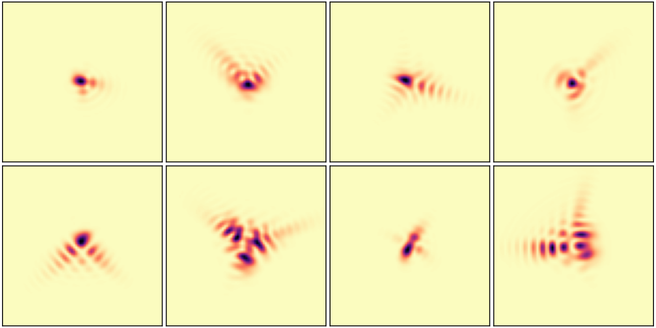
Example of Diffraction PSF

Elementary PSF



Example of Diffraction PSF

Random PSF



Blind deconvolution–Problem formulation

Modeling the image acquision

The acquisition model reads

$$y = S_s Q_q \left(\mathcal{P}_\gamma \left(h(\theta) \star x \right) + \epsilon_\sigma \right), \tag{2}$$

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

Blind deconvolution

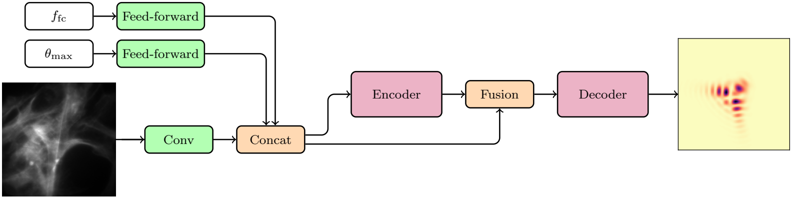
Estimating h and x from y.

PSF Identification

Estimating h from y.

Identification Network

Architecture: auto-encoder like architecture



≈ 60 million parameters.

Identification Network

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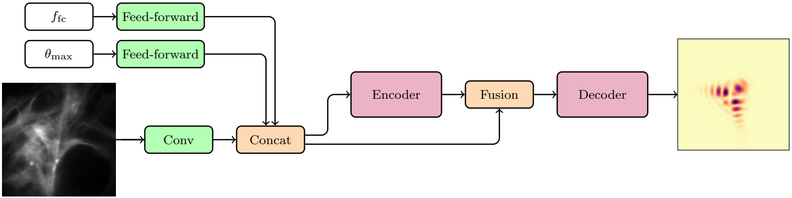

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Supervised training

Simulate random parameters $(\theta_{\max}, \gamma, \sigma, f_{\text{fc}})$ following μ, synthesize $\boldsymbol{y}$ following (2) and solve:

$$\min_{w} \mathbb{E}_{\mu,\boldsymbol{x}} \left[\|\hat{\boldsymbol{h}} - h(\boldsymbol{\theta})\|_1 \right] + \lambda \mathbb{E}_{\mu,\boldsymbol{x}} \left[\|\hat{\boldsymbol{h}} \star \boldsymbol{x} - \boldsymbol{y}\|_1 \right], \tag{3}$$

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

Pseudo-code of the training procedure

Algorithm Training the PSF identification neural network

Require: μ, λ, batch size B, number of iterations N

Initialize the neural networ N_w
for $i \leftarrow 1$ to N **do**
    Sample a random mini-batch x
    Sample random parameters $(\theta_{\max}, \gamma, \sigma, f_{\mathrm{fc}})$ following μ
    Synthesize $y = S_s Q_q \left(\mathcal{P}_\gamma \left(h(\theta) \star x \right) + \epsilon_\sigma \right)$
    Compute the loss (3)
    Update the network N_w by gradient descent
end for

Numerical results

On synthetic data

	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

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

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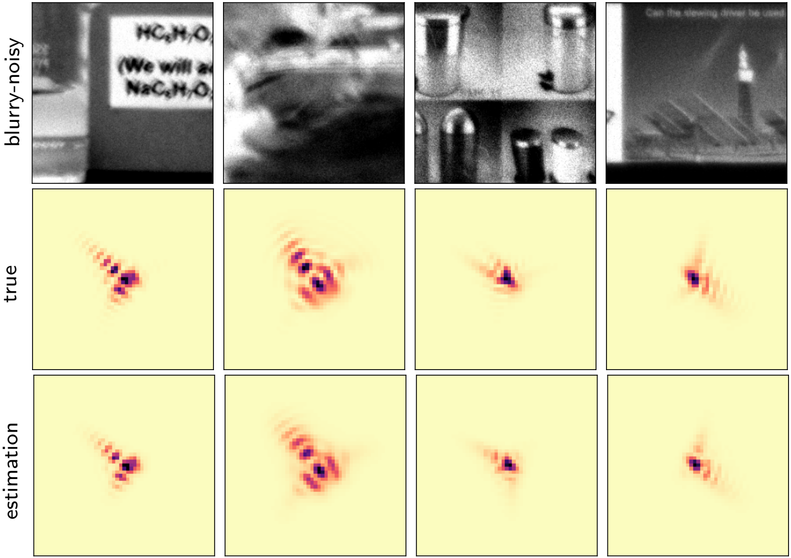
Slight performance drop when f_{fc} and $\theta_{\max}$ are unknown.

Numerical results

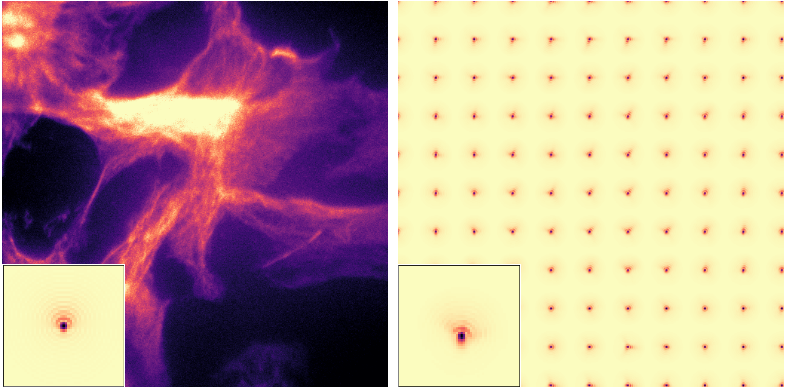
Example on ImageNet



Numerical results

Real data: Fluorescence TIRF Microscopy

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



Images of microtubules and Estimated PSF grids

Numerical results

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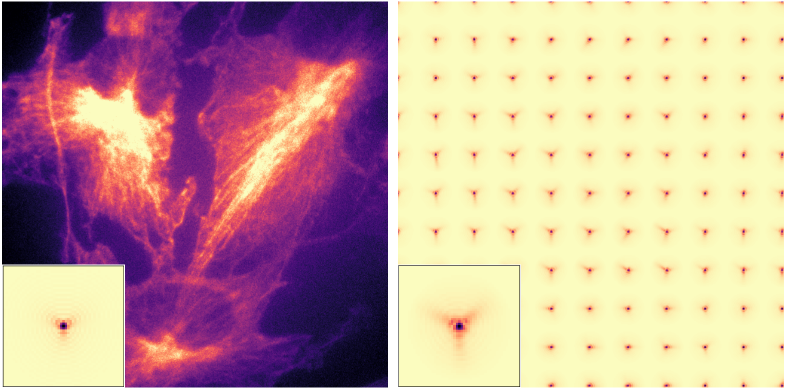

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Thank you for your attention!