Semi-Blind Spatially-Variant Deconvolution in Optical Microscopy with Local Point Spread Function Estimation by Use of Convolutional Neural Networks

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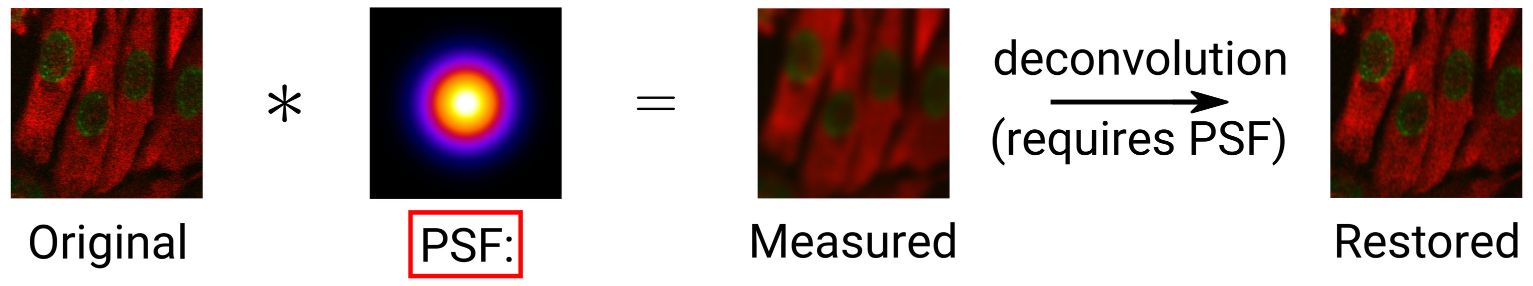
Is it possible to train a system to characterize the local degradation of an image, so it can be improved ?



?
- cumbersome to measure experimentally
- spatially varying
- changes from microscope to microscope

We present a spatially-variant blind deconvolution technique aimed at microscopy of thin, yet non-flat objects. Our method combines **local determination of the point spread function** (PSF) and **spatially-variant deconvolution** using a regularized Richardson-Lucy (RL) algorithm. To find the space-variant PSF in a computationally tractable way, we train a **convolutional neural network** to perform regression of model parameters on synthetically blurred images.

Step 1: set a parametric model for the degradation

We develop a parametric model for the optical system allowing the generation of PSFs.

$$h_{\mathbf{a}}(\mathbf{s}) = |\mathcal{F}(W_{\mathbf{a}}(\mathbf{s}))|^2 \qquad W_{\mathbf{a}}(\mathbf{s}) = \sum_{k=0}^{K-1} a_k \cdot Z_k(\mathbf{s})$$

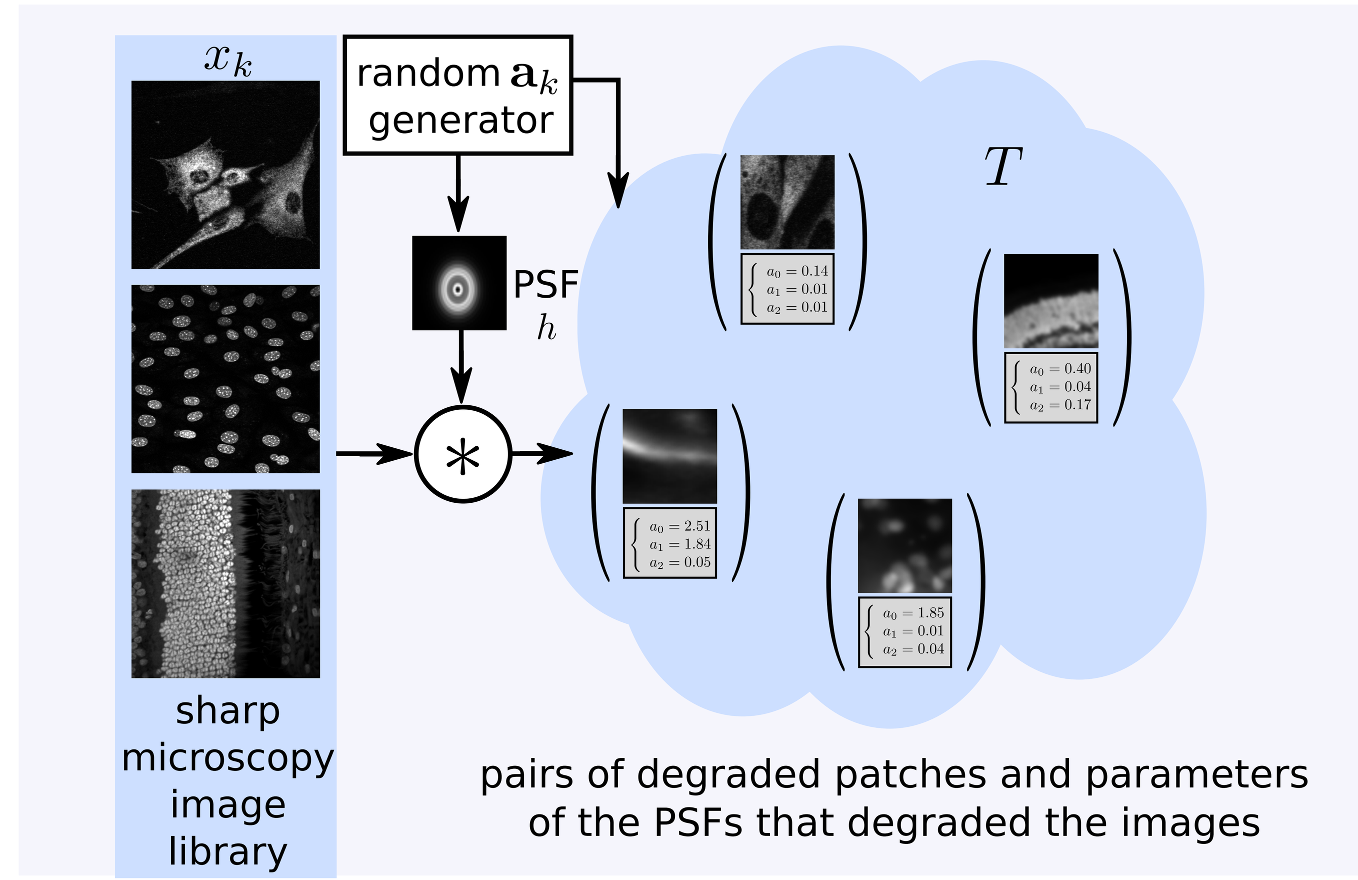
Point spread function (PSF) from Zernike polynomial coefficients

k	$Z_k(\mathbf{s}) = Z_k(\theta,\rho)$	Aberration name
0	$\sqrt{3}(2\rho^2-1)$	Defocus
1	$\sqrt{6}\rho^2(sin 2\theta)$	Astigmatism
2	$\sqrt{5}(6\rho^4-6\rho^2+1)$	Spherical aberration
...	...	...

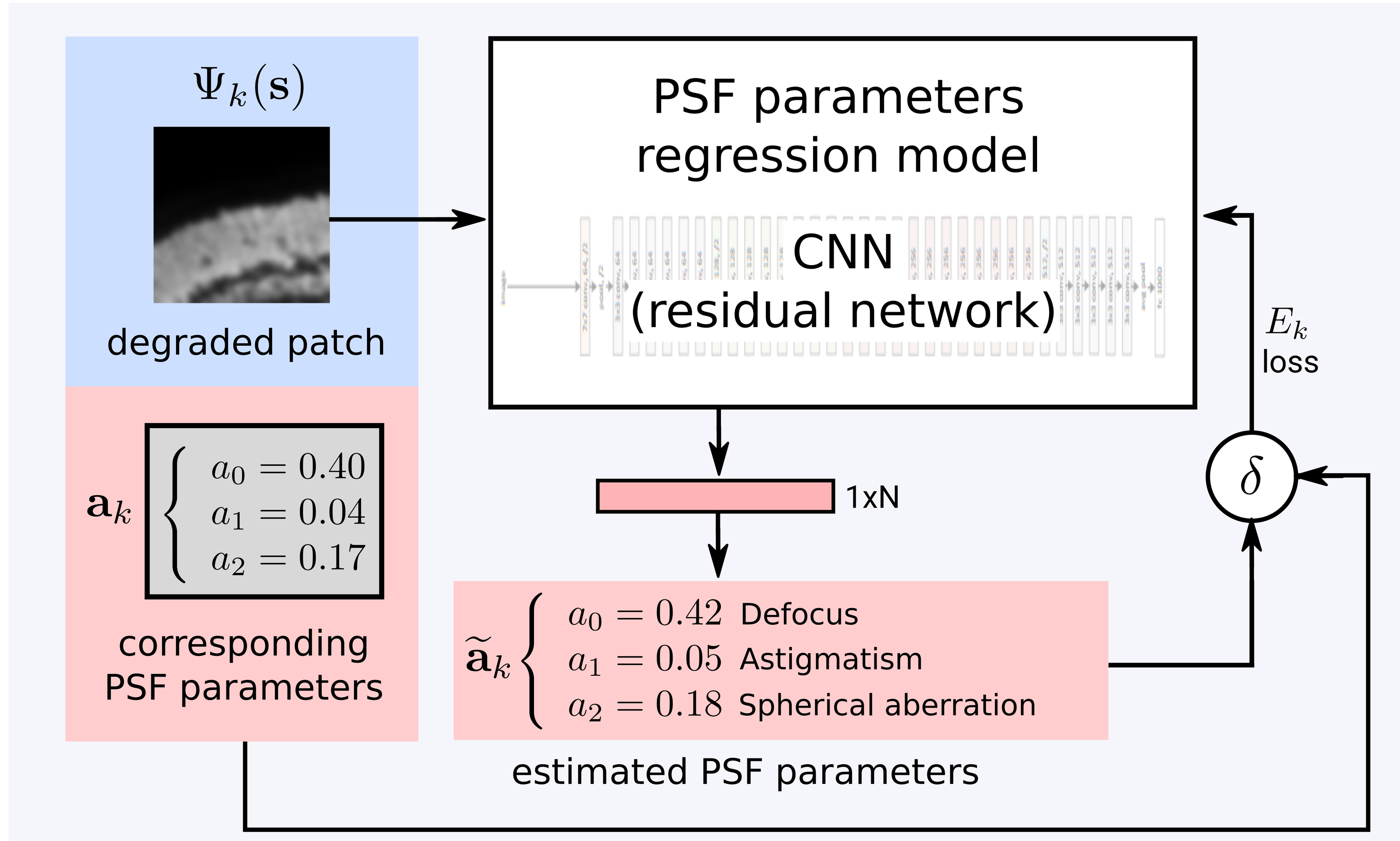
Step 2: generate training library of degraded images

Sharp training images are degraded with PSFs of known parameters:

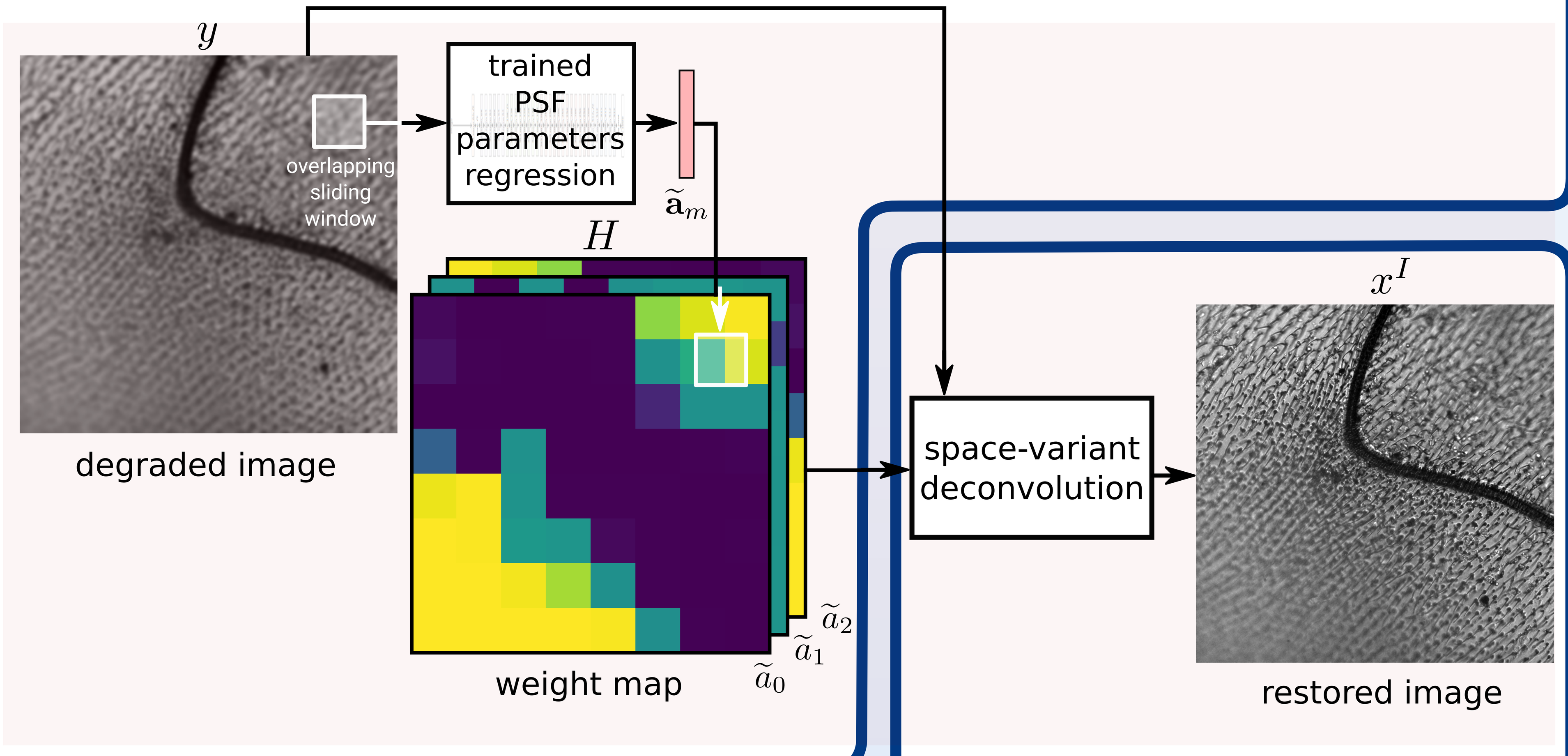
$$\Psi_k(\mathbf{s}) = (h_{\mathbf{a}_k} * x_k)(\mathbf{s}) = \mathcal{F}^{-1}[\mathcal{F}(h_{\mathbf{a}_k})\mathcal{F}(x_k)](\mathbf{s})$$



Step 3: train a CNN to estimate PSF parameters



Step 4: use trained CNN to retreive the local PSF parameter map



Step 5: perform spatially-variant deconvolution using PSF map

Deconvolution using a combination of overlap-add filtering and regularized Richardson-Lucy (RL) algorithm: (i) cover the image with overlapping patches using interpolation, (ii) convolve each patch with a different PSF, (iii) add the patches to obtain a single large image (*Hirsch et al.*, 2010).

$$x(\mathbf{s}) = \mathcal{F}^{-1}\left[\sum_m^M \mathcal{F}(h_m(\mathbf{s})) \cdot \mathcal{F}(\varphi_m(\mathbf{s}) \cdot y(\mathbf{s}))\right],$$

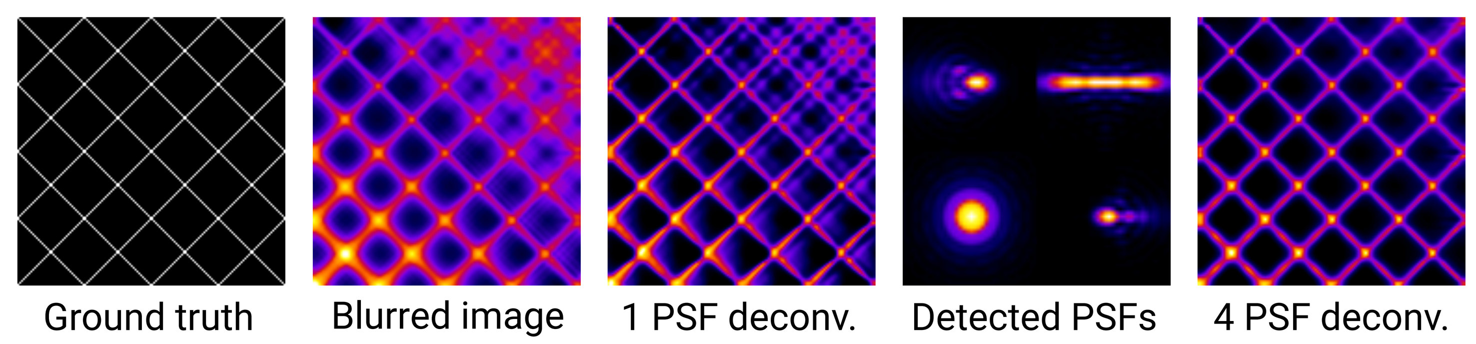
with h_m the m-th filter, φ_i the mask for patch m, y the input image, and x the filtered output image.

Integrating Total Variation (TV) regularization (*Dey et al.*, 2006), the final iterative output is:

$$x^{i+1}(\mathbf{s}) = \sum_m^M \left[\frac{(h_m * (\varphi_m \cdot y))(\cdot)}{(h_m * x_m^t)(\cdot)} * h_m(-\cdot)\right](\mathbf{s}) \cdot \frac{x_m^i(\mathbf{s})}{1 - \lambda_{TV}\,\mathrm{div}\left(\frac{\nabla x_m^i(\mathbf{s})}{|\nabla x_m^i(\mathbf{s})|}\right)}$$

with λ_{TV} the regularization factor and i the RL iteration index.

Results: we can recover a local map of the PSFs that degraded the image



Using a generated grid pattern degraded by four randomly-generated PSFs, we assessed the reconstruction quality compared to (1) *Holmes et al.*, 1995, (2) *Kotera et al.*, 2013 and (3) *Whyte et al.*, 2014.

$\mathrm{SNR}_{\mathrm{degraded}}$	$\mathrm{SNR}_{\mathrm{ours}}$	$\mathrm{SNR}_{(1)}$	$\mathrm{SNR}_{(2)}$	$\mathrm{SNR}_{(3)}$
1.90 dB	**4.48 dB**	3.48 dB	1.4 dB	1.54 dB
$\mathrm{SSIM}_{\mathrm{degraded}}$	$\mathrm{SSIM}_{\mathrm{ours}}$	$\mathrm{SSIM}_{(1)}$	$\mathrm{SSIM}_{(2)}$	$\mathrm{SSIM}_{(3)}$
0.10	**0.51**	0.28	0.29	0.52

Conclusions

- We were able to detect the original blur kernel with a regression accuracy of 0.91, given only synthetic images as the training input (no experimental measurement of the PSF was necessary).
- We have been able to deconvolve with an SNR on average 1.00 dB higher than other blind deconvolution techniques.
- We validated our approach on experimental data and observed a visual improvement similar or, in some regions, better than when we used other methods.

Advantages:
- Our approach does not require any experimental PSF measurement.
- The regression network is real-time once trained (a few hours).
- Parameters with a physical meaning are inferred from the image.
- Training set and PSF model can be adapted to specific applications.

Limitations:
- The number and type of regressed Zernike polynomials have an important influence on the performance.
- The model takes into account only thin, yet non-flat objects.

Software

The code is available at https://github.com/idiap/semiblindpsfdeconv.

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