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

Adrian Shajkofci1,2, Michael Liebling1,3
1Computational Bioimaging Group, Idiap Research Institute, Martigny, Switzerland
2Electrical Engineering Doctoral Program, EPFL, Lausanne, Switzerland
3Electrical and Computer Engineering Department, University of California, Santa Barbara, USA

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

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.

\[ h(s) = |F\{w(s)\}|^2 \]

\[ w(s) = \sum_{k} \alpha_k z_k(s) \]

Point spread function (PSF) from Zernike polynomial coefficients

Aberration name | Zernike coefficients
--- | ---
Defocus | \[ \sqrt{3}(x^2 - 1) \]
Astigmatism | \[ \sqrt{2}x \sin(2\theta) \]
Spherical aberration | \[ \sqrt{2}(y^2 - y^2 + 1) \]

Step 2: generate training library of degraded images
Sharp training images are degraded with PSFs of known parameters:

\[ w(s) = (h_{\text{true}} * z_k)(s) = F^{-1}[F(h_{\text{true}})F(z_k)](s) \]

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Step 3: train a CNN to estimate PSF parameters

![CNN diagram](image)

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 other blind deconvolution techniques.

\[ \text{SNR}_{\text{degraded}} = 1.90 \text{ dB} \]
\[ \text{SNR}_{\text{prop}} = 4.48 \text{ dB} \]
\[ \text{SNR}_{\text{true}} = 1.45 \text{ dB} \]

\[ \text{SSIM}_{\text{degraded}} = 0.50 \]
\[ \text{SSIM}_{\text{prop}} = 0.29 \]
\[ \text{SSIM}_{\text{true}} = 0.29 \]

**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.
- The regression network is real-time once trained (a few hours).
- It is easy to implement.

**Limitations**
- The number and type of regressed Zernike polynomials have an important influence on the performance.
- Training set and PSF model can be adapted to specific applications.

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

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Funded by Swiss National Science Foundation 200020 179217 Computational biomicroscopy: advanced image processing methods to quantify live biological systems (2018–2022), SNF 205021_154422 R’Equip and Valais-Wallis Ambition Initiative.