Spatially Variable Deconvolution for Lightsheet Microscopy

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LIGHTSHEET MICROSCOPY

TODO: a few words about why lightsheet is good
Light sheet microscopy is a type of fluorescence microscopy used in cell biology due to its fast acquisition times and low photo-damage to the sample. This is achieved by selectively illuminating a slice of the sample using a sheet of light and detecting the emitted fluorescence signal using a dedicated objective orthogonal to the plane of the sheet.

- Project aim: computationally improve the quality of light sheet microscopy images.

Light-sheet microscope

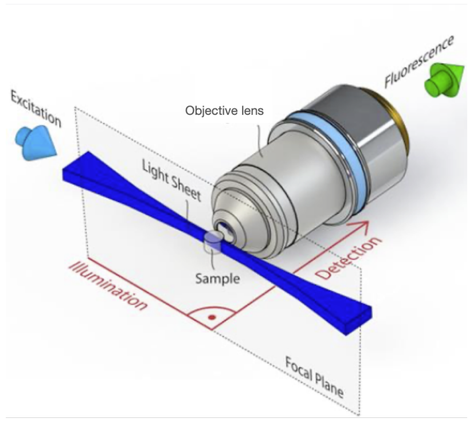
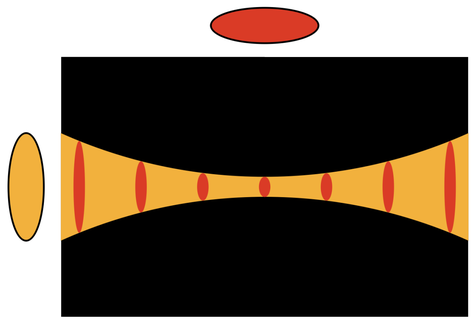


Figure credit: Jörg Ritter, PhD thesis (2011)

A light-sheet microscope consists of two objectives: TODO etc

Spatially varying PSF



Problem

Due to the combination of light-sheet and the objective PSF, the effective PSF of the system is spatially varying, and therefore standard deconvolution approaches are not applicable.

PSF MODEL

TODO We calculate the objective PSF h by using a model that includes defocus etc etc.
TODO: reference to paper

$$h(x,y,z) = \left| \iint g_\sigma * p(\kappa_x,\kappa_y) e^{2i\pi z\sqrt{(n/\lambda)^2-\kappa_x^2-\kappa_y^2}} e^{2i\pi(\kappa_x x+\kappa_y y)} \,\mathrm{d}\kappa_x \,\mathrm{d}\kappa_y \right|^2 \quad (1)$$

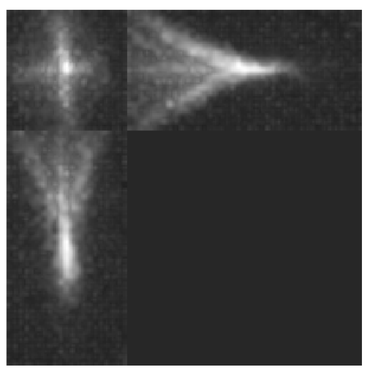
with the pupil function p defined

$$p(\kappa_x,\kappa_y) = \begin{cases} e^{2i\pi\sum_{j=1}^{15} c_i Z_j(\kappa_x,\kappa_y)} & \text{for} \quad \rho = \sqrt{\kappa_x^2+\kappa_y^2} \le NA/\lambda, \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

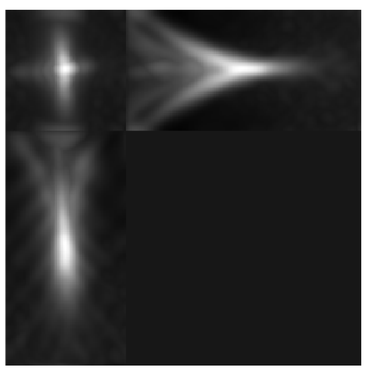
where the phase of the pupil function is computed by least-squares fitting of the coefficients of the first 15 Zernike polynomials using an image of a bead.

The parameters of the model are given by the experimental setup used to acquire the image:

- n - refractive index
- λ - wave length
- NA - numerical aperture
- g_σ Gaussian blur to take into account other properties not accounted for in our model



Bead image (MIP)



Estimated objective PSF (MIP)

IMAGE FORMATION MODEL

The sample s illuminated at $z = z_0$ by the light-sheet l and the photons are collected by an objective with PSF h:

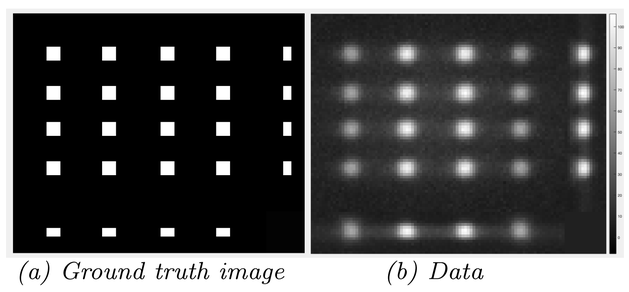
$$f(x,y,z_0) = \iiint l_{avg_y}(u,v,w) s(u,v,w-z_0) h(x-u,y-v,w) \,\mathrm{d}u \,\mathrm{d}v \,\mathrm{d}w$$

where h is given in (1) and l is calculated similarly (TODO explain)
TODO: insert diagram of the image formation to explain the forward model

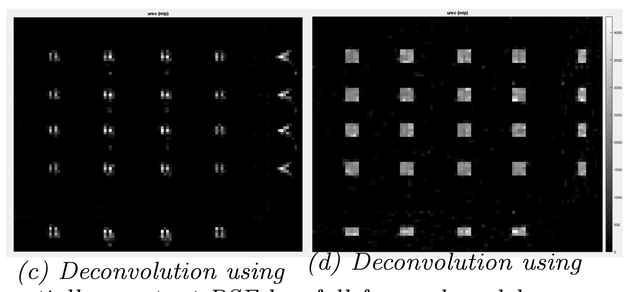
RECONSTRUCTION

Let $\hat{f}$ be the image data and $f(s)$ the result of applying the forward model to the sample s. To recover s, we solve:

$$\text{Find } \hat{s} \in \operatorname{argmin}_s \left\{ \|\hat{f} - f(s)\|_{L_2} + \lambda TV(s) \right\}$$



(a) Ground truth image *(b) Data*



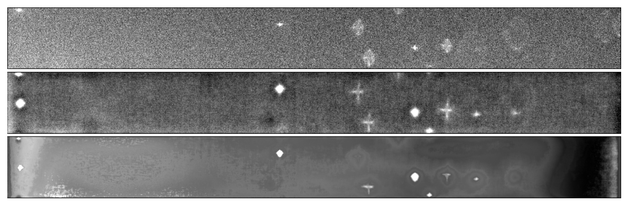
(c) Deconvolution using spatially constant PSF h *(d) Deconvolution using full forward model.*

- To solve the optimisation problem, we apply a version of the Primal Dual Hybrid Gradient (PDHG) algorithm TODO:reference
- In the figure on the left, we show an example of a simulated sample (a) to which we apply the forward model with Gaussian noise (b) and the result of deconvolving using only a spatially varying PSF (c) and the full forward model (d).

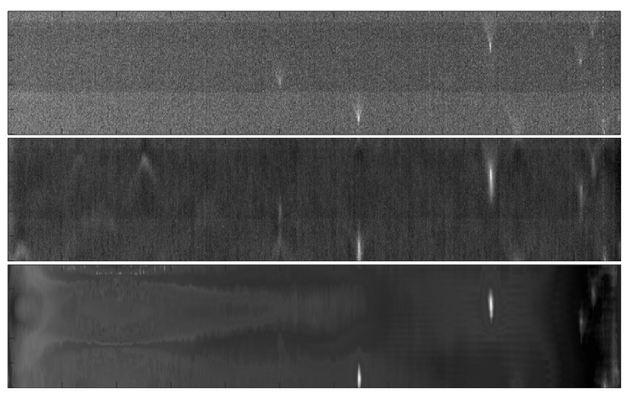
Results

Beads

Full resolution image: 1127 x 111 x 100



Data (top), constant PSF deconvolution (middle), model deconvolution (bottom)



Data (top), constant PSF deconvolution (middle), model deconvolution (bottom)

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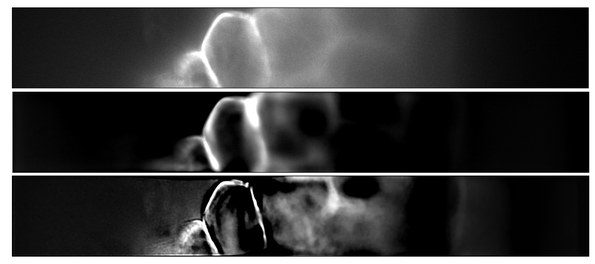
Full resolution image: 1127 x 155 x 100



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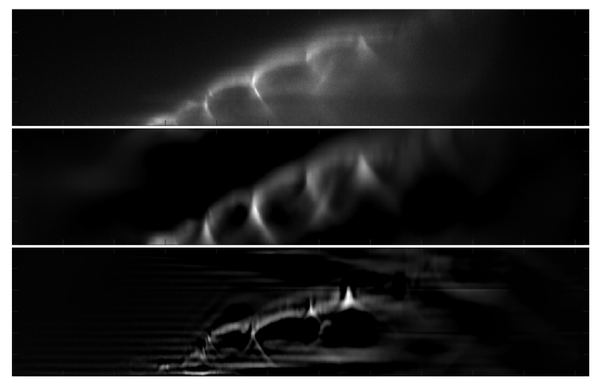

Data (top), constant PSF deconvolution (middle), model deconvolution (bottom)

References

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