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.

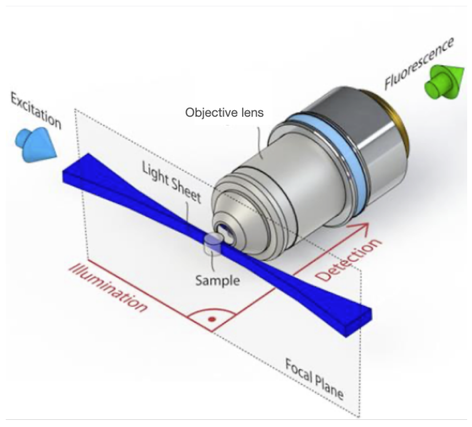
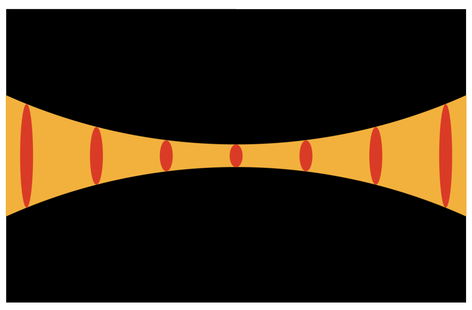


Figure credit: Jörg Ritter, PhD thesis (2011)

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

Spatially varying PSF



Problem

Due to the combination of light-sheet beam (yellow) and the objective PSF (red), 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

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

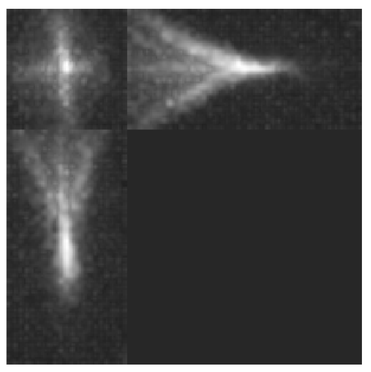
with the pupil function p defined

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

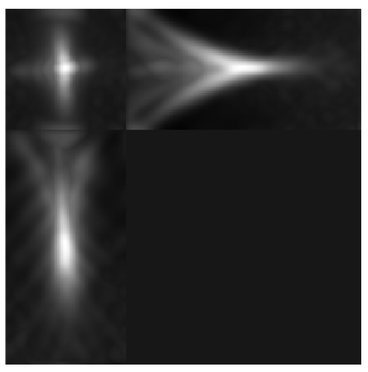
where the phase of the pupil function is computed by least-squares fitting of the coefficients of the first 15 Zernike polynomials using an image of a bead.

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



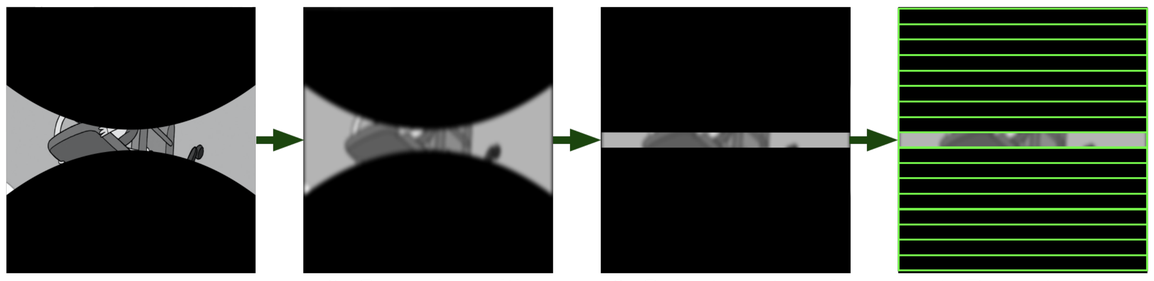
Bead image (MIP)



Estimated objective PSF (MIP)

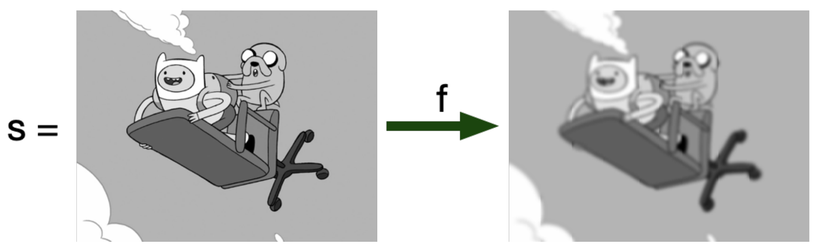
IMAGE FORMATION MODEL

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



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

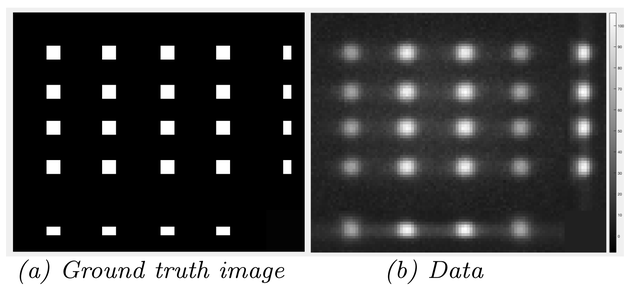
where h is the objective PSF, calculated using (1) and l_{avg_y} is the light-sheet, calculated by averaging the beam PSF obtained in a similar way to h, without Zernike polynomials.



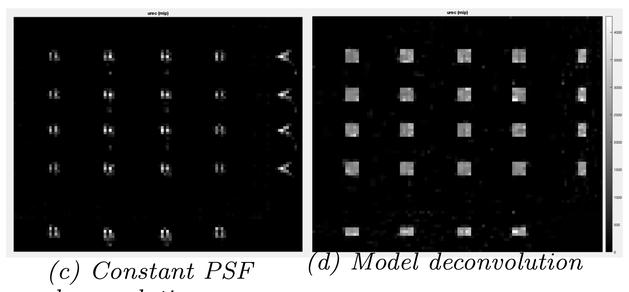
RECONSTRUCTION

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:

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



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



(c) Constant PSF deconvolution *(d) Model deconvolution*

- 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

- We apply the proposed method to a sample of beads in agarose.
- The dimensions of the sample are 1127 x 111 x 100 pixels.
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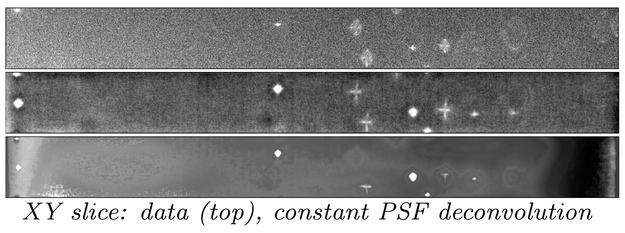
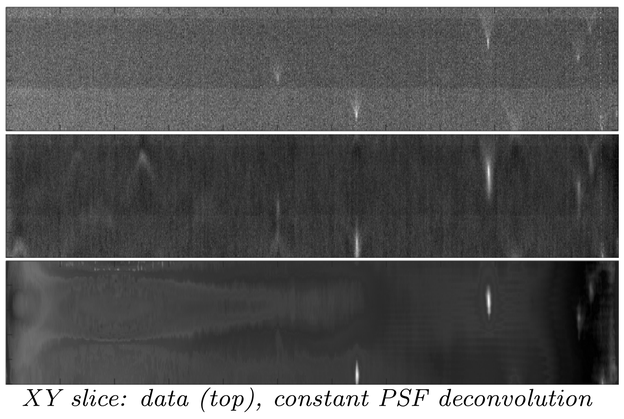


XY slice: data (top), constant PSF deconvolution (middle), model deconvolution (bottom)



XY slice: data (top), constant PSF deconvolution (middle), model deconvolution (bottom)

Marchantia

- We apply the proposed method to a sample of Marchantia plant.
- The dimensions of the sample are 1127 x 155 x 100 pixels.
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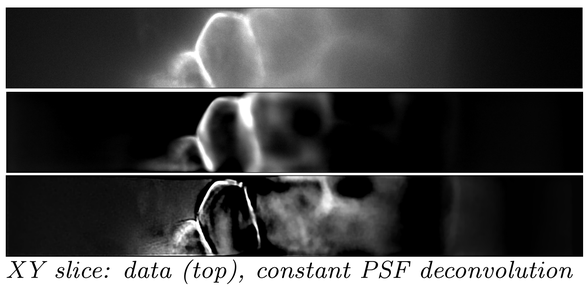
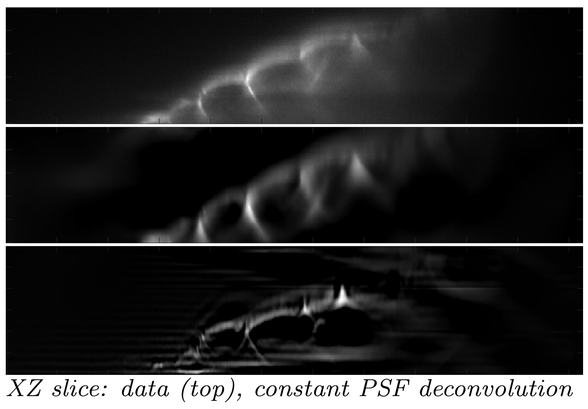


XY slice: data (top), constant PSF deconvolution (middle), model deconvolution (bottom)



XZ slice: data (top), constant PSF deconvolution (middle), model deconvolution (bottom)

References

Acknowledgments

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