

# Improving Resolution in Wide-field Fluorescence Microscopy Using Deconvolution Techniques

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*Electrical and Computer Engineering, UCSB*

*Funding Source: Hellman Fellowship granted to Dr. Michael Liebling*

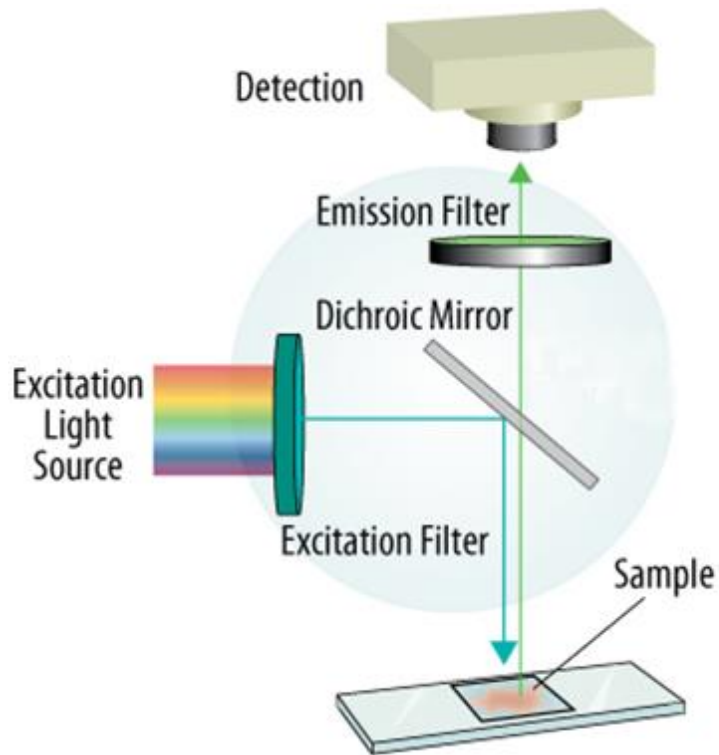


**Systems Bioimaging Lab**  
**Development**

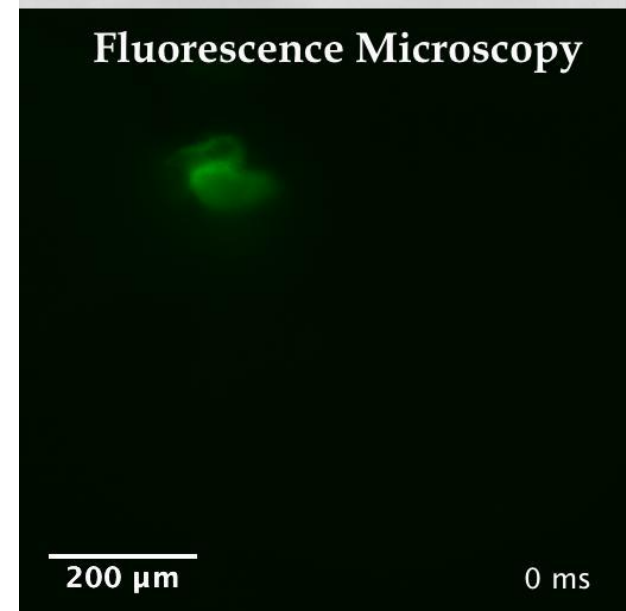
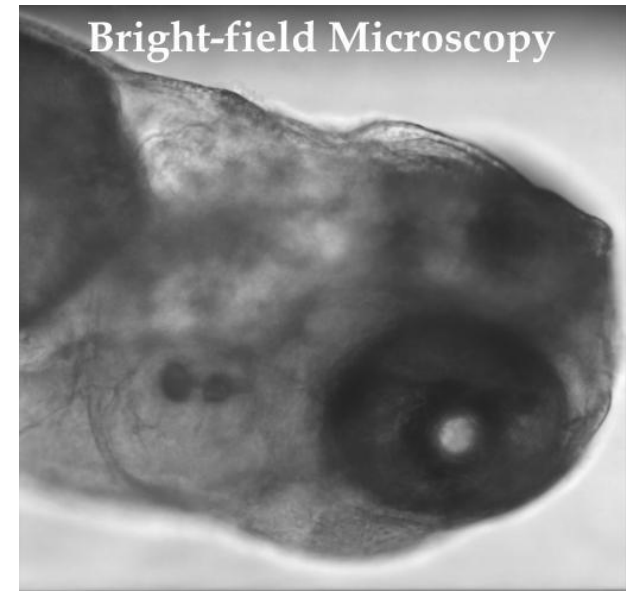


# Fluorescence Imaging

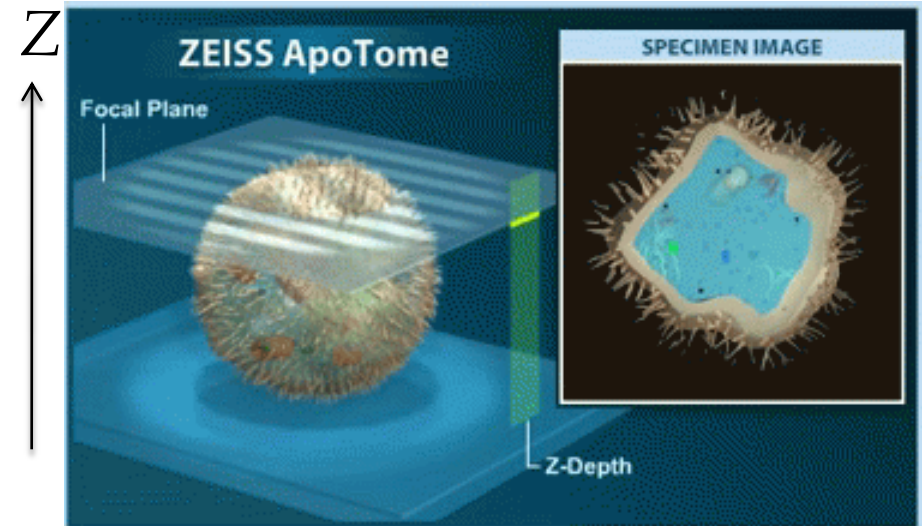
## Simplified Model of Fluorescence Imaging



# Fluorescence is exploited in Fluorescence Microscopy



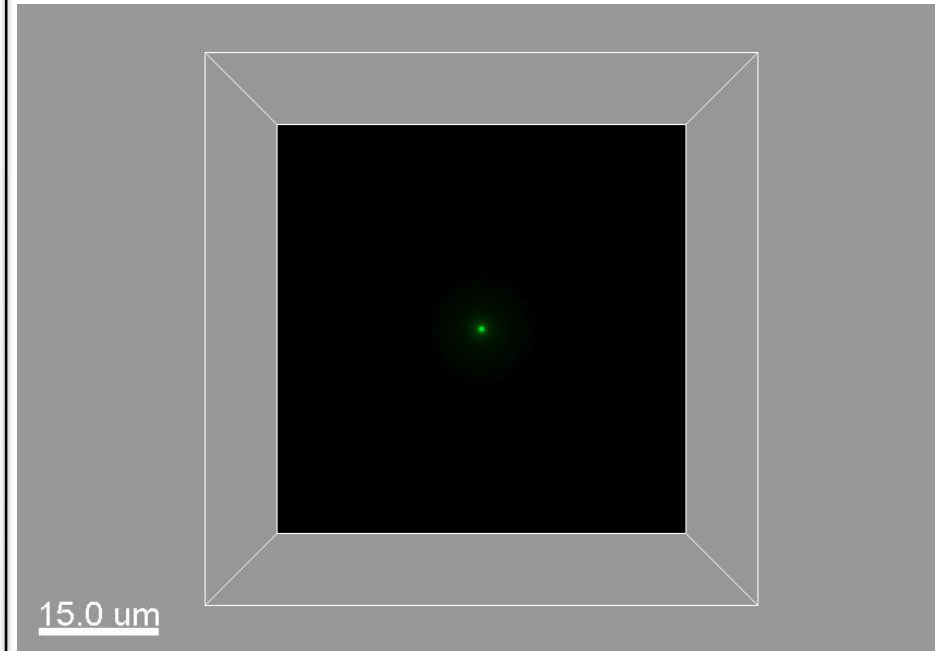
# We acquire 3D datasets by **Optical Sectioning Microscopy**



## Drawbacks

- Out-of-focus adjacent planes contaminate image.
- Bad axial ( $z$ ) resolution.

A point source that exists in only one focal plane along  $z$  spreads to other focal planes:  
**Point Spread Function (PSF)**

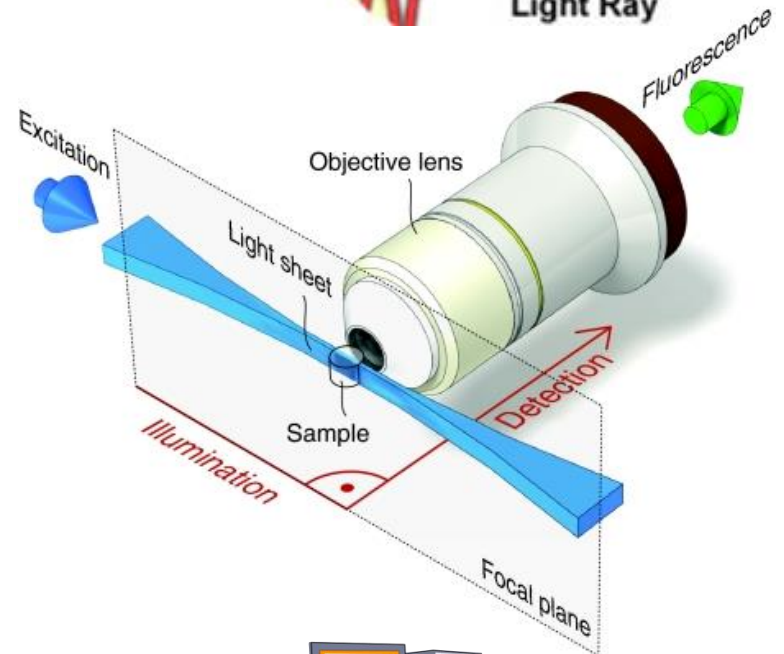
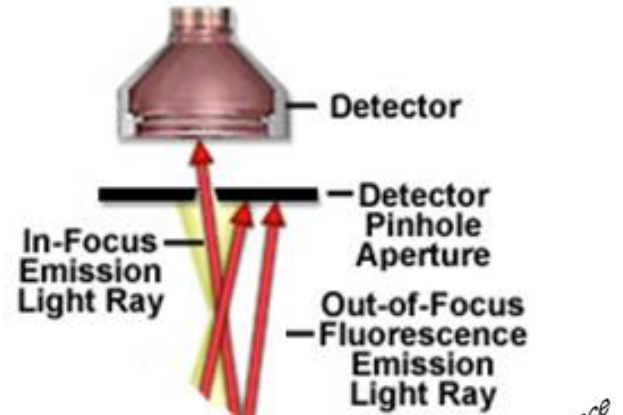


# We can alleviate the blur by:

(a) Illuminating the whole sample and using a physical barrier to block rogue light rays.  
(*Confocal Microscopy*)

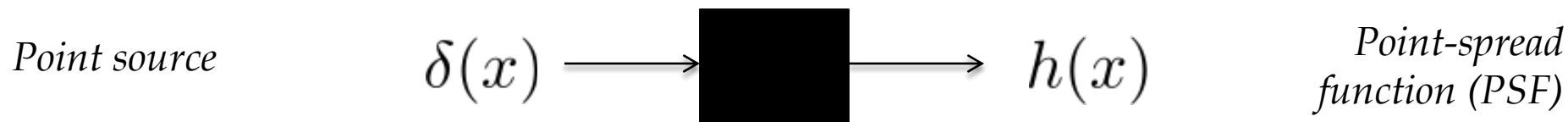
(b) Restricting the excitation to the plane of interest alone.  
(*Light-sheet Microscopy*)

(c) Image processing  
(*Deconvolution*)



# Deconvolution methods assume a **shift-invariant model**

A shift-invariant system is completely characterized by its response to a point source:



*Any signal can be represented as a linear combination of many points.*

*Any signal response can be represented as a linear combination of many PSFs.*



Fourier Transforms simplify convolutions to multiplications

$$F(\omega) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\xi) \cdot e^{-j\omega\xi} d\xi$$

$$G(\omega) = F(\omega) \cdot H(\omega)$$

Given  $f(x)$  and  $h(x)$ , find  $g(x)$ : convolution problem

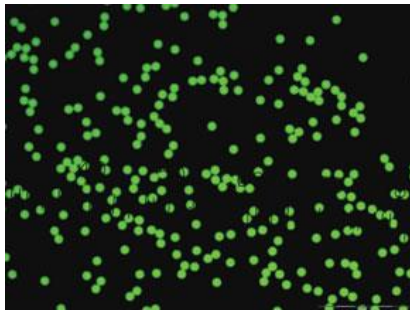
Given  $g(x)$  and  $h(x)$ , find  $f(x)$ : **deconvolution** problem

# Project Steps

- 1. Model the available microscope (Leica DMI 6000B)**  
Determine the PSF characteristic to the microscope in the lab.
- 2. Deconvolve data from Single-View observation**  
Use PSF to deblur 3-D data acquired by the microscope.
- 3. Deconvolve data from Multi-View observation**  
Acquire data from multiple angles and perform deblurring using a multi-channel deconvolution algorithm.

# 1. PSF determination

Fluorescent beads having a diameter less than the spatial resolution of the device approximate point sources.

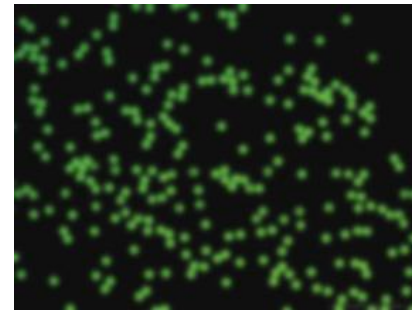


fluorescent beads



Leica DMI6000b

The blurred observation of any single bead hints to the PSF of the microscope.

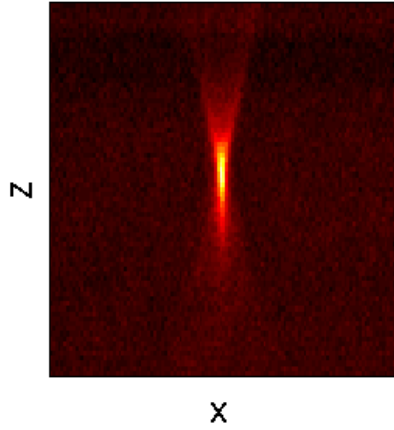


blurred observation

# 3D PSF Intensity Graphs ( $x$ - $z$ plane)

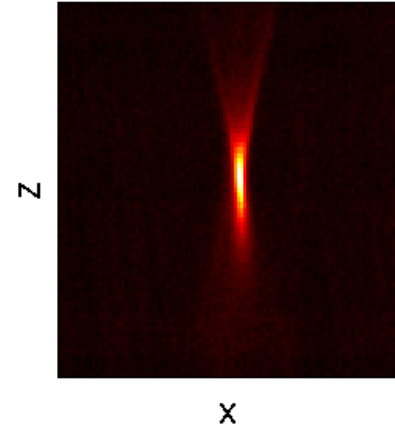
*Comparison of measured PSF to theoretical models*

*A single measured PSF exhibits significant amount of noise.*



Measured PSF

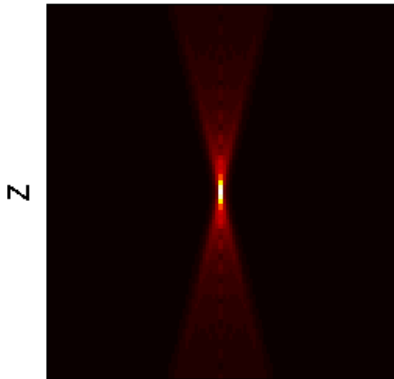
*Average over multiple similar data*



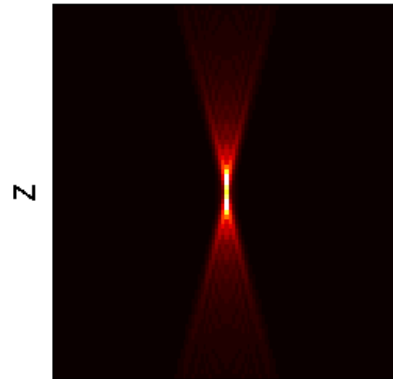
Averaged PSF

*Averaging reduces the standard deviation of the noise component, improving signal quality.*

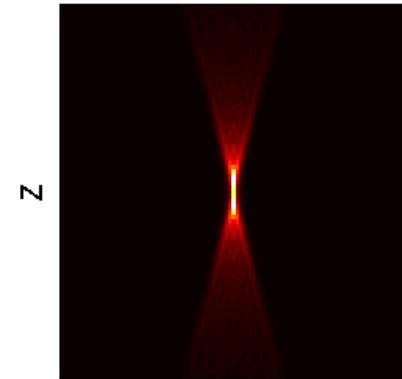
Theoretical models generated according to parameters in experimental setup:



Born & Wolf PSF

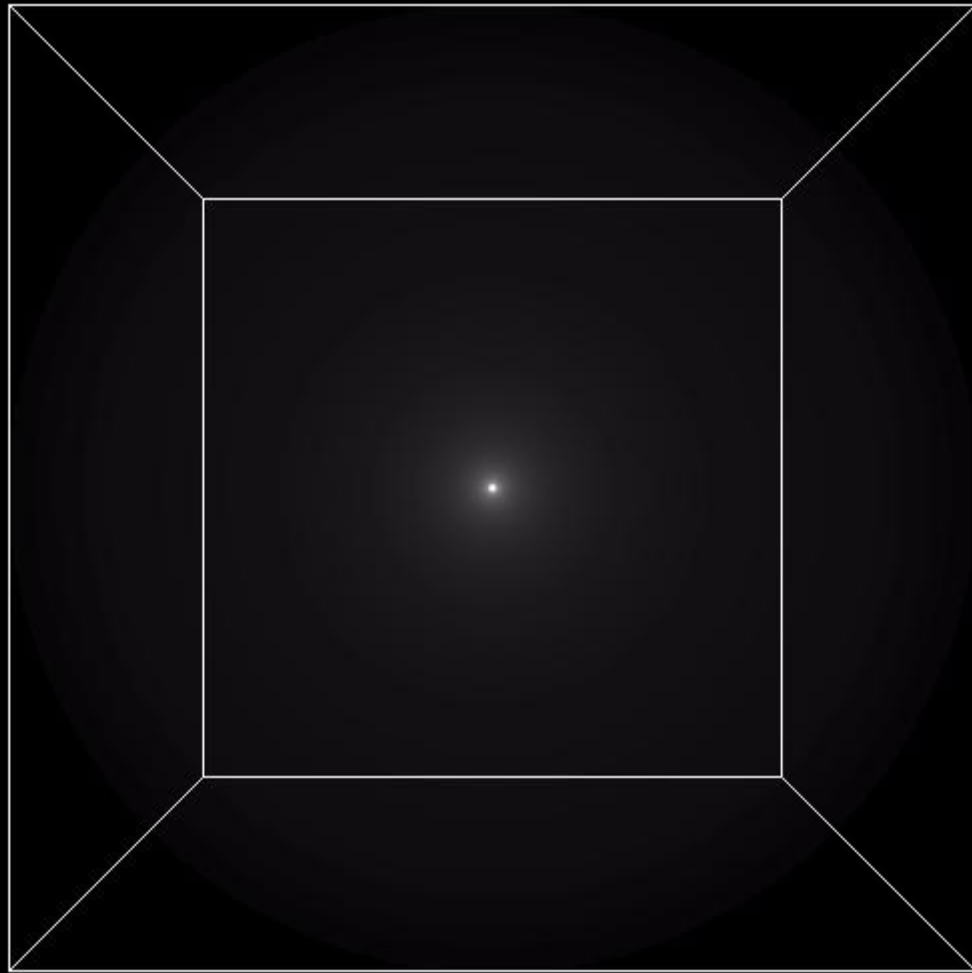


Gibson & Lanni PSF



Richards and Wolf PSF

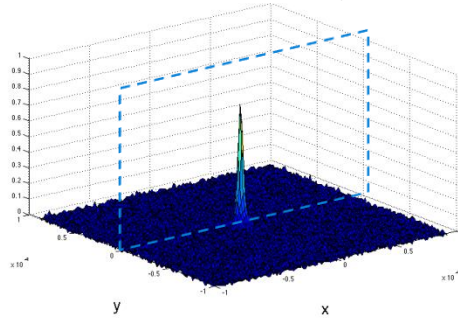




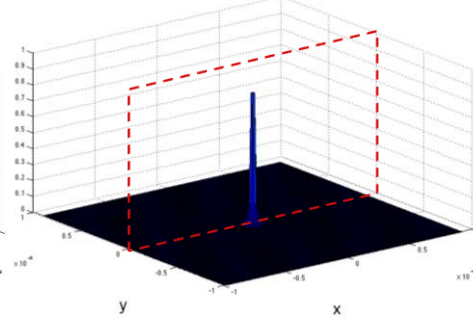
15.0  $\mu\text{m}$

# 3D PSF Intensity Graphs ( $x$ - $y$ plane)

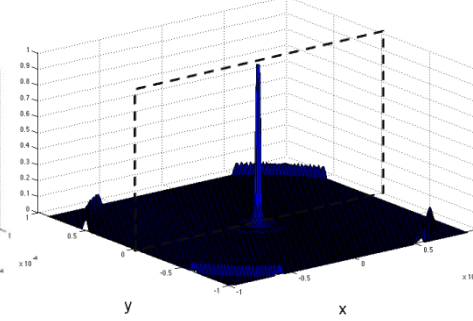
Comparison of measured PSF to theoretical models



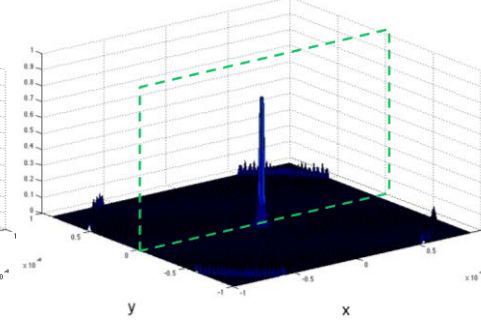
Measured PSF  
(averaged)  
in  $x$ - $y$  plane  
at  $z = 0 \mu\text{m}$



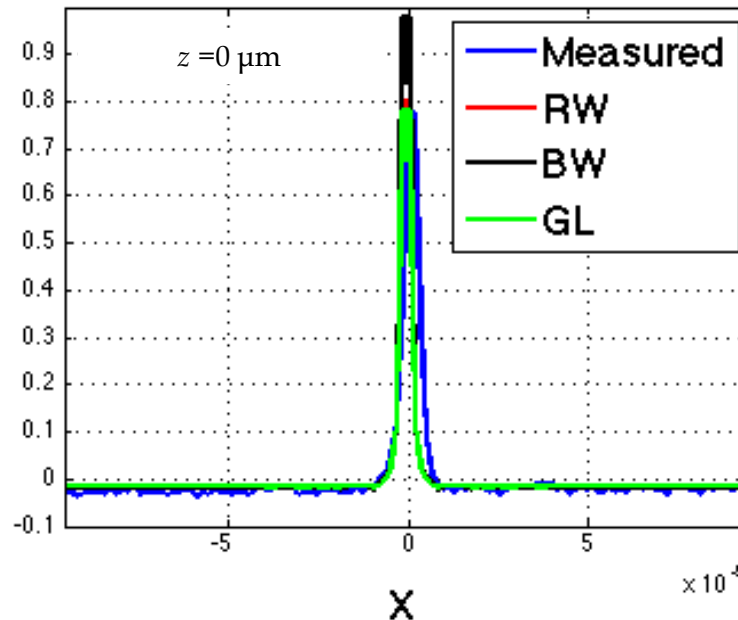
Richards-Wolf (RW)  
PSF Model  
in  $x$ - $y$  plane  
at  $z = 0 \mu\text{m}$



Born-Wolf (BW)  
PSF Model  
in  $x$ - $y$  plane  
at  $z = 0 \mu\text{m}$



Gibson-Lanni (GL)  
PSF Model  
in  $x$ - $y$  plane  
at  $z = 0 \mu\text{m}$

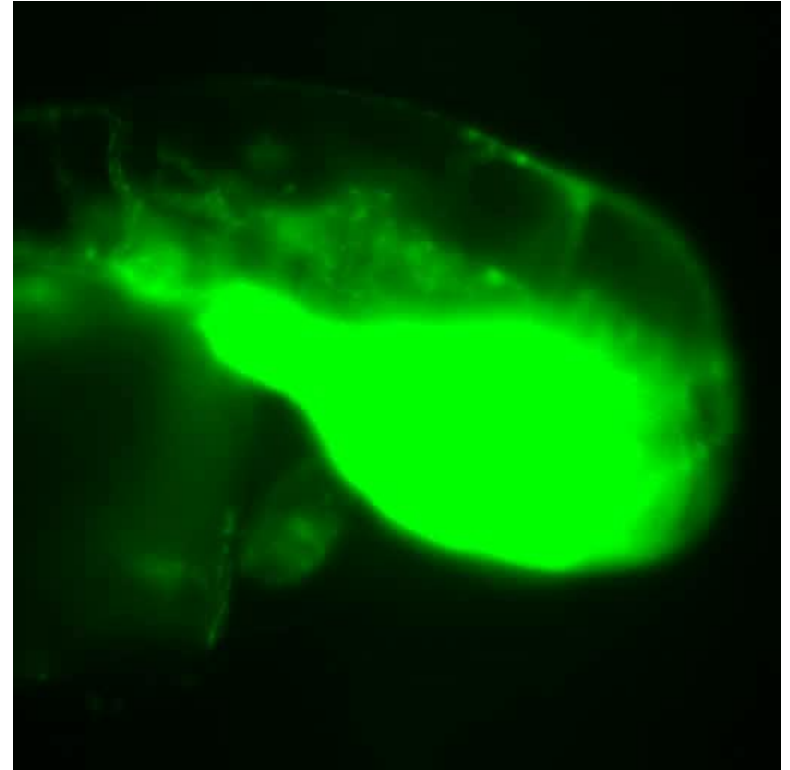


## 2. Deconvolve data from Single-View observation

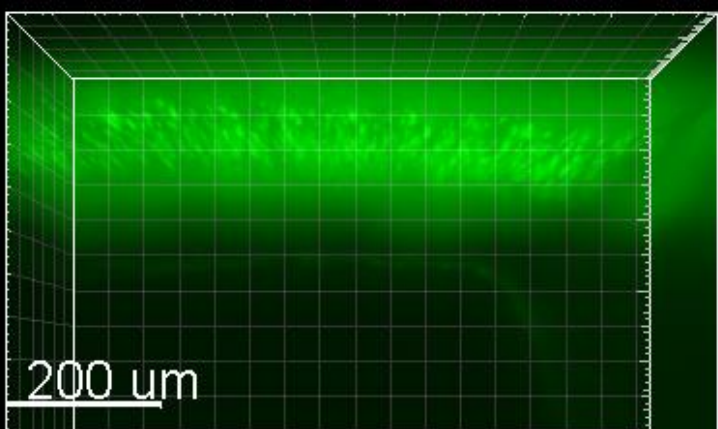
Zebrafish Tg(f1ia:EGFP), fluorescent along the vertebral column, was used in the experimental setup for imaging.



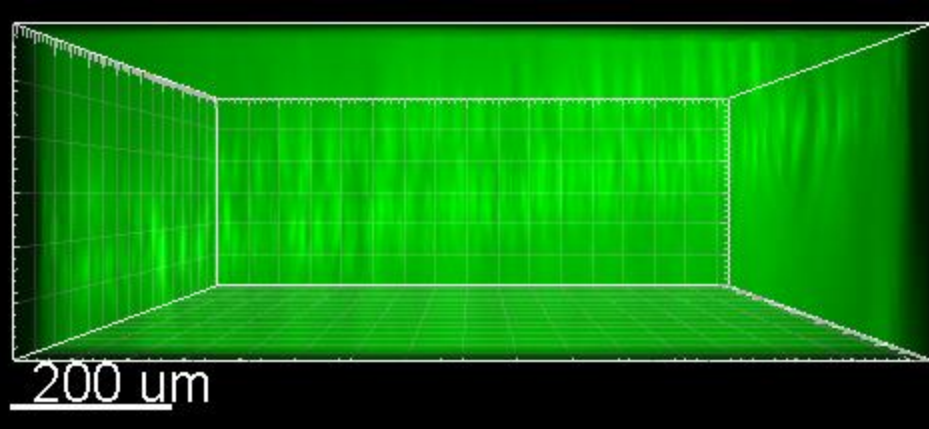
Bright-field Microscopy



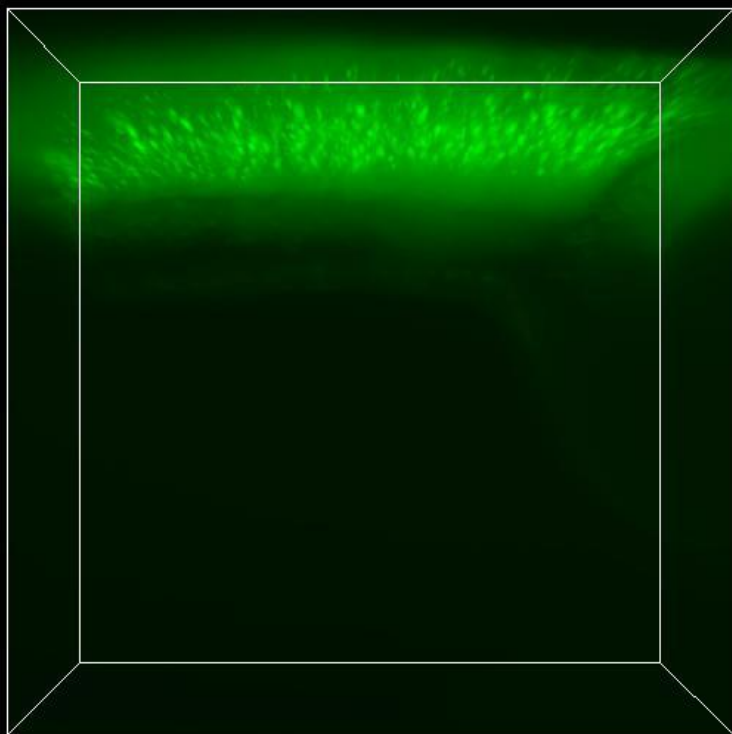
Fluorescence Microscopy



*xy-plane*

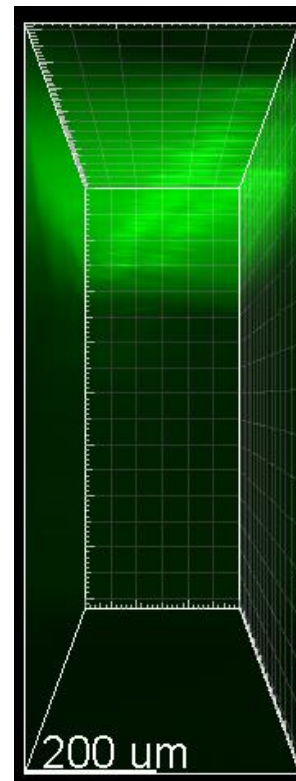


*xz-plane*



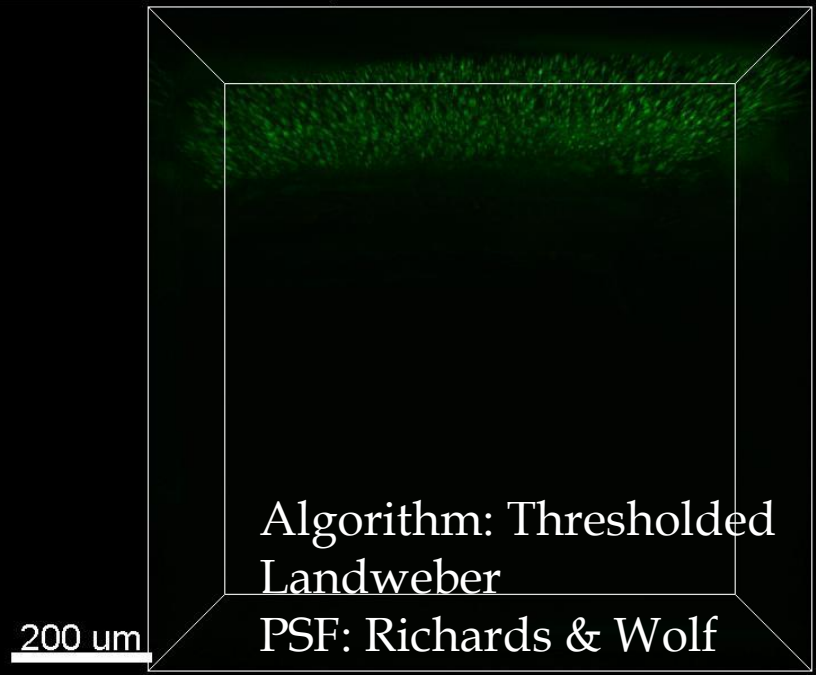
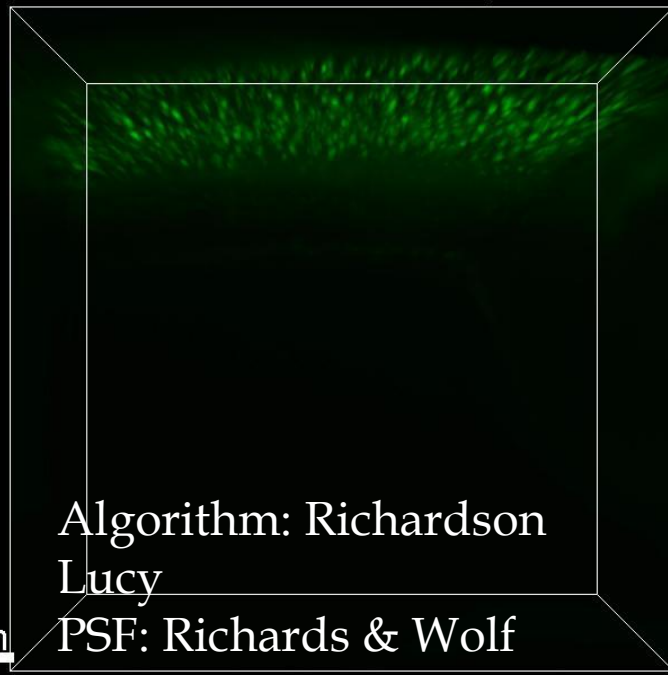
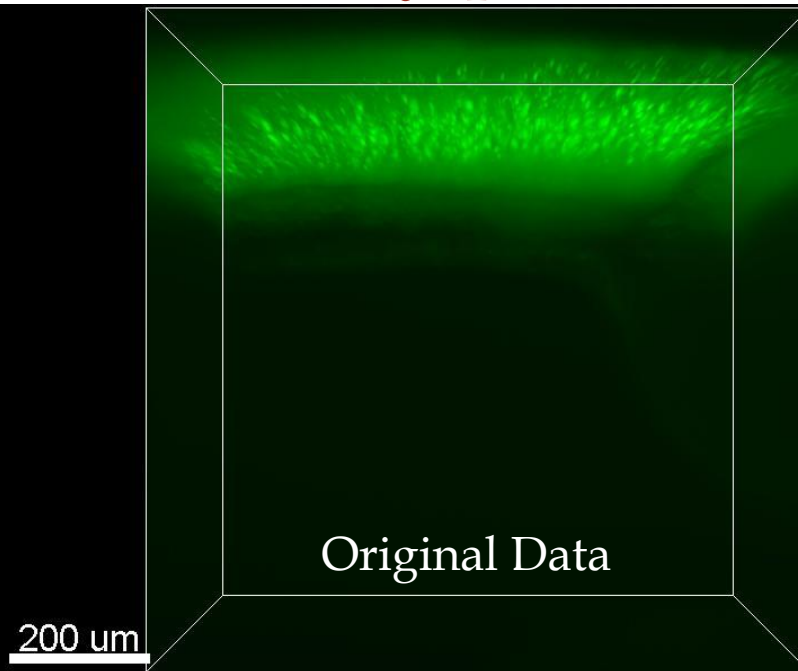
200  $\mu\text{m}$

*yz-plane*

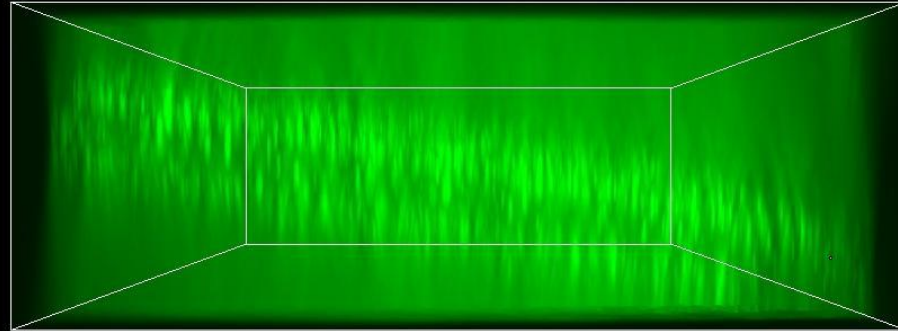


200  $\mu\text{m}$

# Deconvolution Results - xy-plane

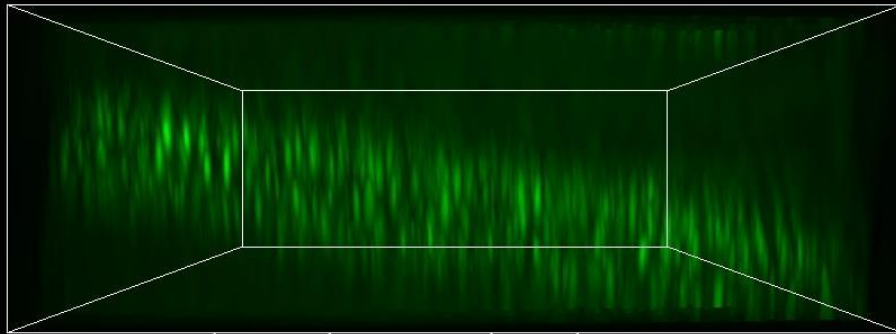


# Deconvolution Results- xz-plane



Original Data

200 um

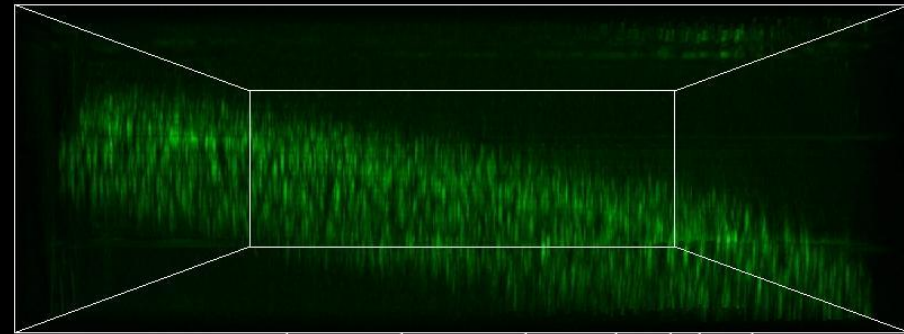


Algorithm: Richardson

Lucy

PSF: Richards & Wolf

200 um



Algorithm: Thresholded

Landweber

PSF: Richards & Wolf

200 um

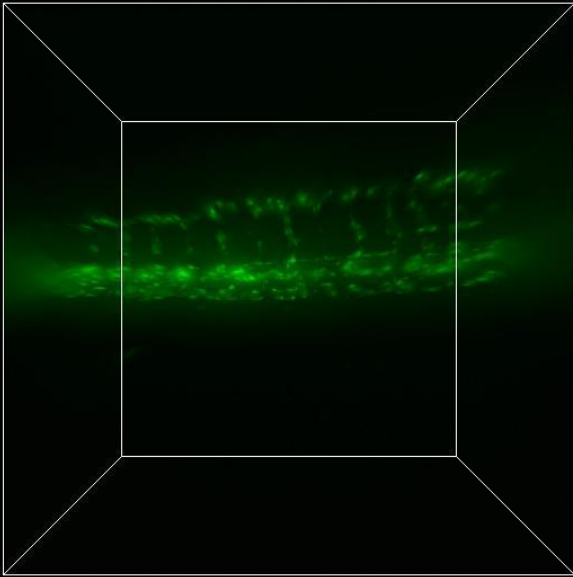
### 3. Deconvolve data from Multi-View observation



We place the specimen within a tube that is connected to a stepper motor. The stepper motor is controlled by an Arduino programming board, which is interfaced to Matlab.

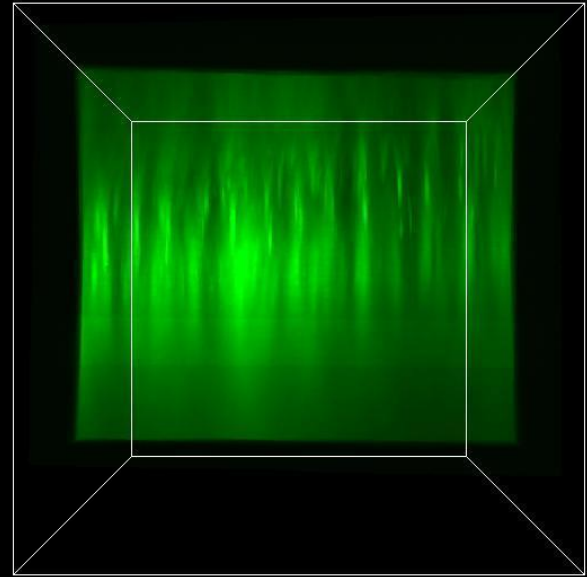
# Zebrafish Multi-View - xy-plane

Angle 0  
(data is  
blurred  
along the  
z-axis)



200 um

Angle 90  
(data is  
blurred  
along the  
y-axis)



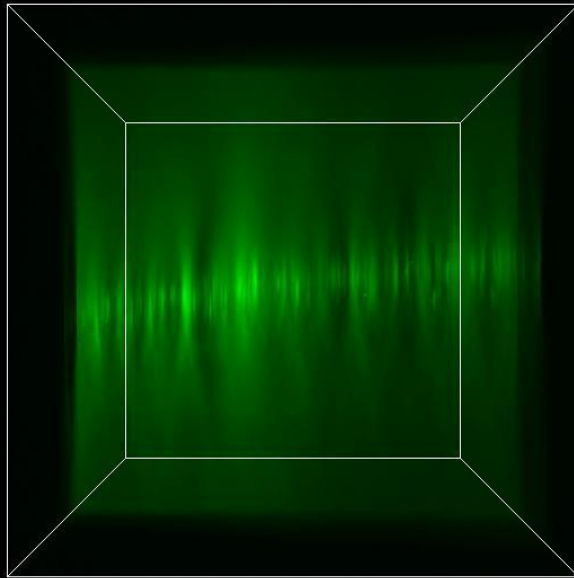
200 um



# Zebrafish Multi-View - xz-plane

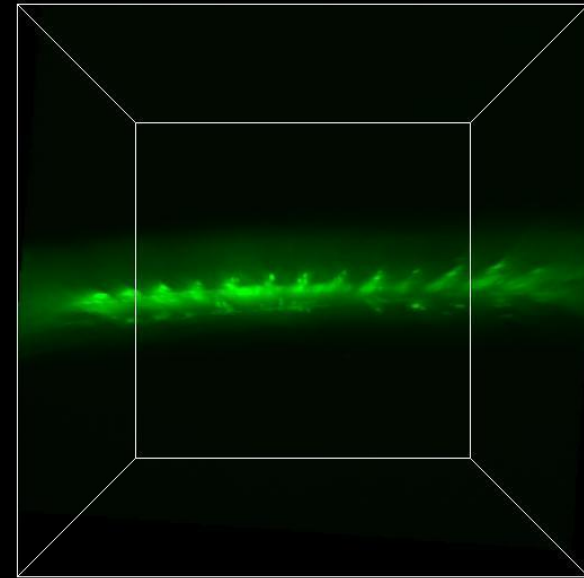
Angle 0  
(data is  
blurred  
along the  
z-axis)

200 um



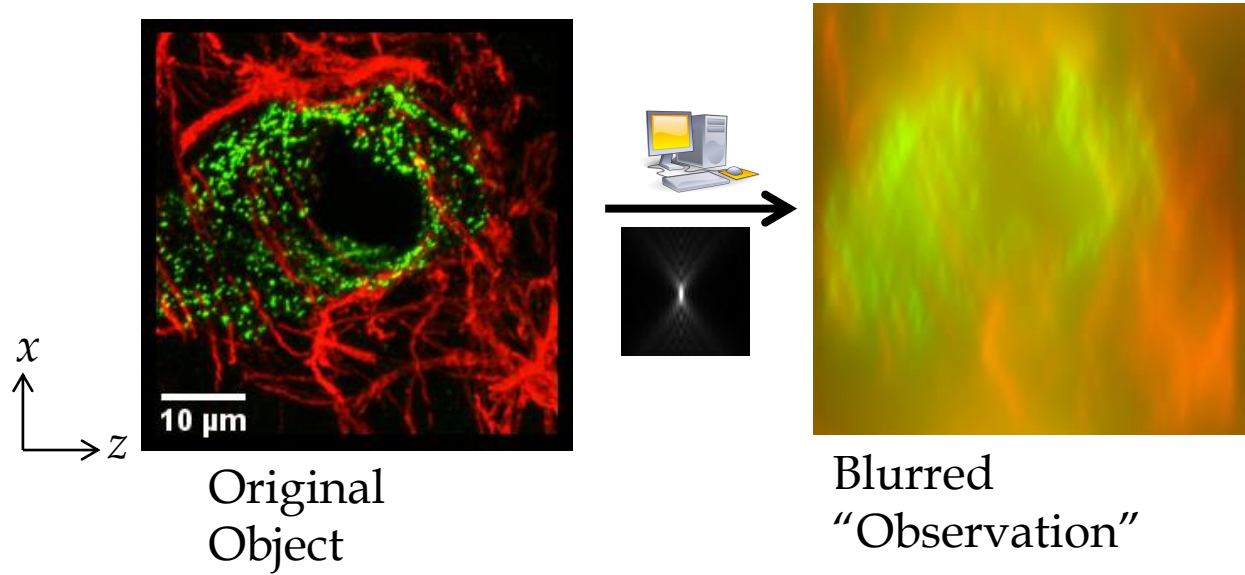
Angle 90  
(data is  
blurred  
along the  
y-axis)

200 um

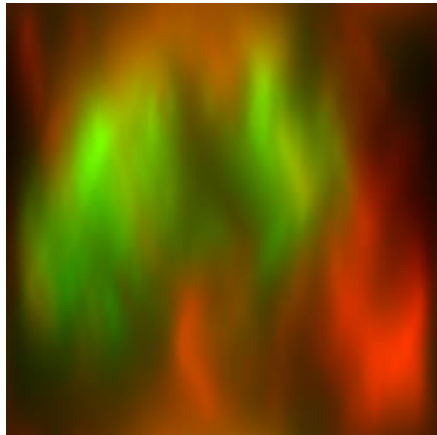


The blur along different directions makes it difficult to spatially register two data sets, making any registration algorithms based on spatial landmarks difficult to use

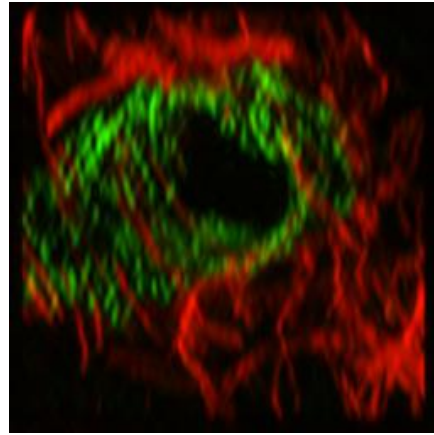
### 3. Deblur data from Multi-View observation (Simulation Results)



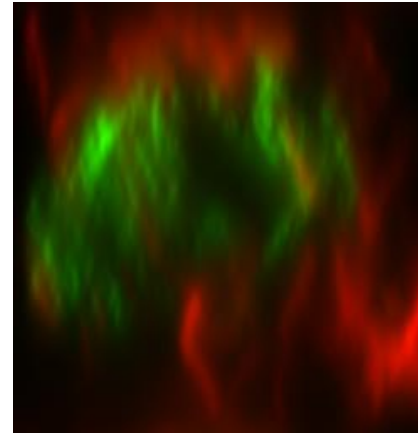
### Single-View Deconvolution Results



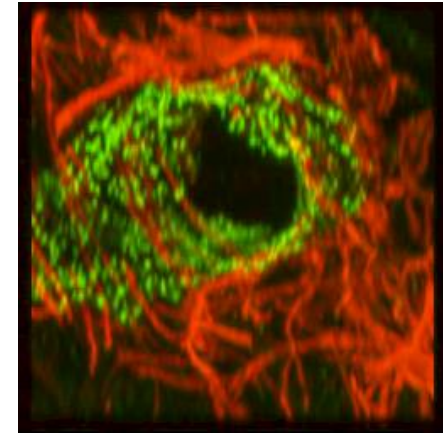
Landweber



Regularized  
Inverse  
Filtering

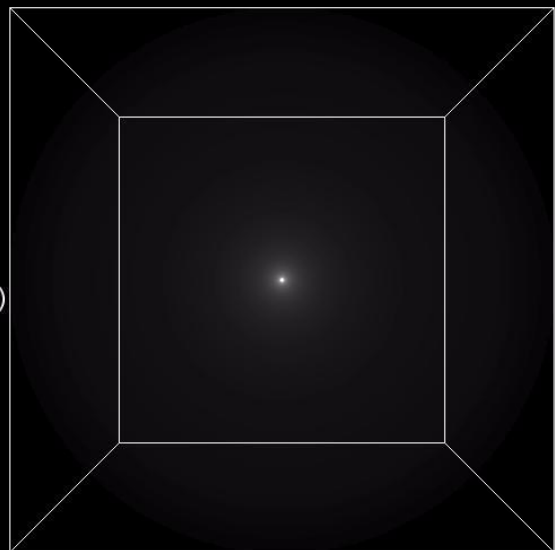


Richardson-  
Lucy



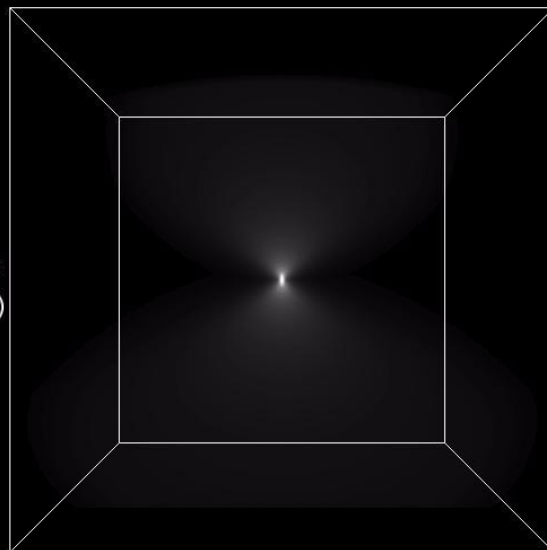
Thresholded  
Landweber

Angle 0  
(max. blur  
along z-axis)



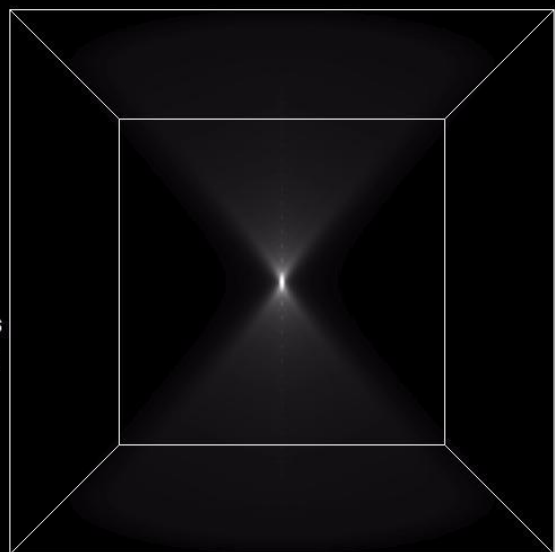
15.0 um

Angle 45  
(max. blur  
45 degrees  
from z-axis)



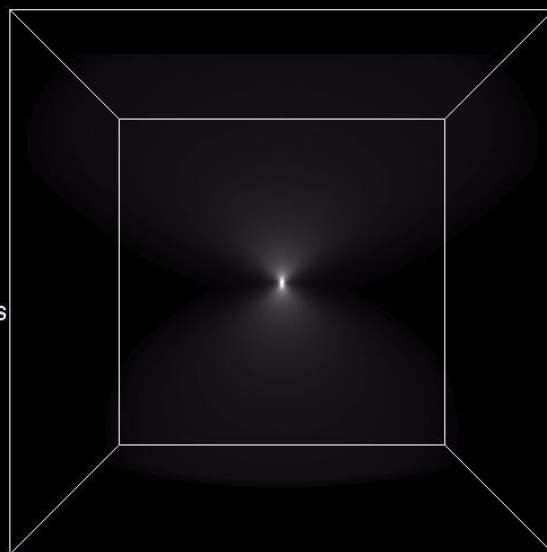
15.0 um

Angle 90  
(max blur  
90 degrees  
from z-axis  
i.e. y-axis)

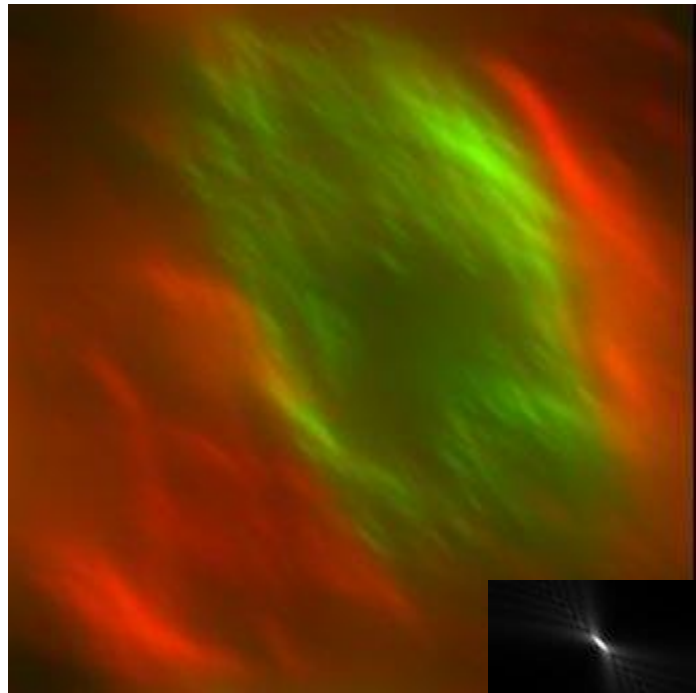
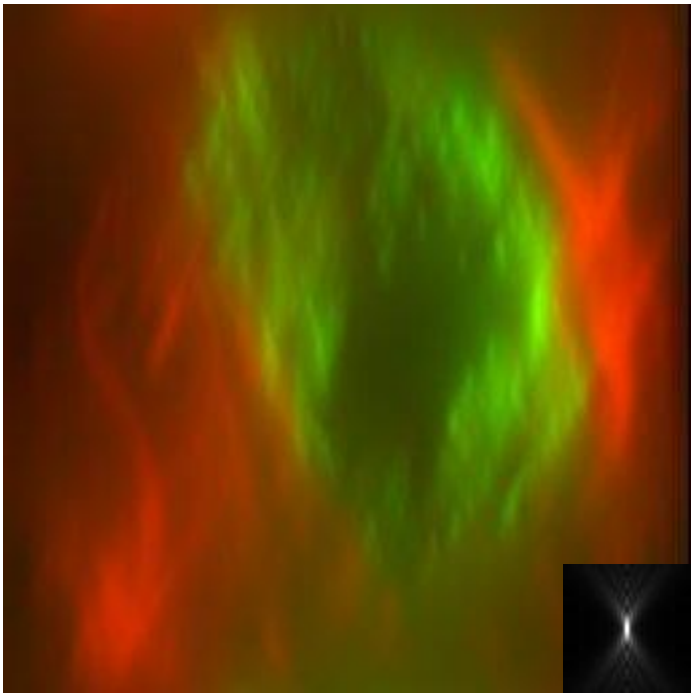
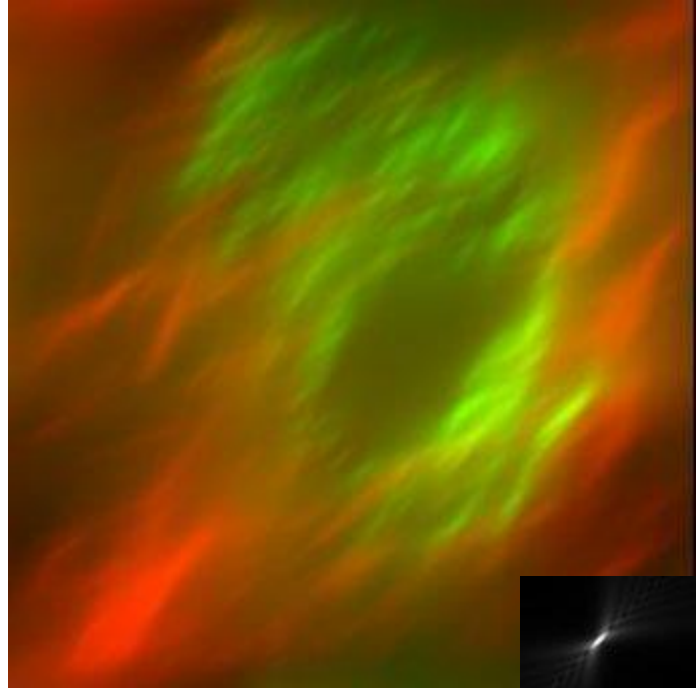
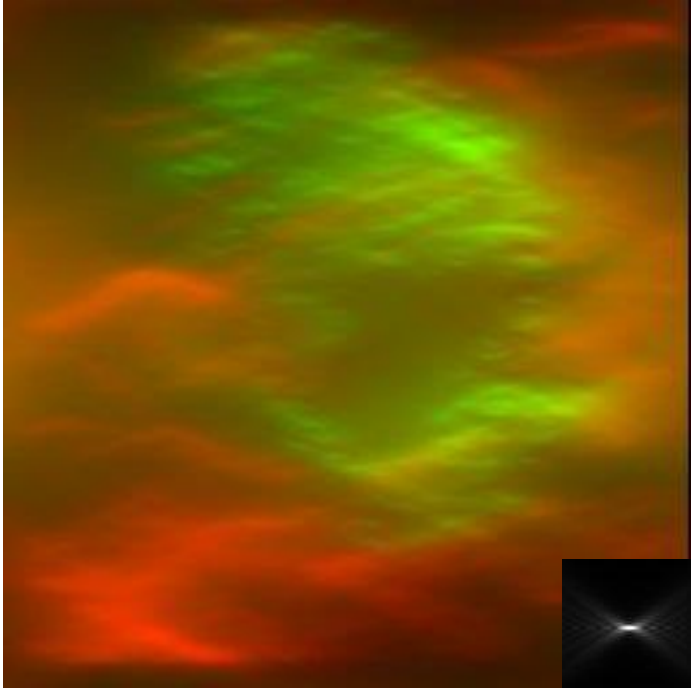


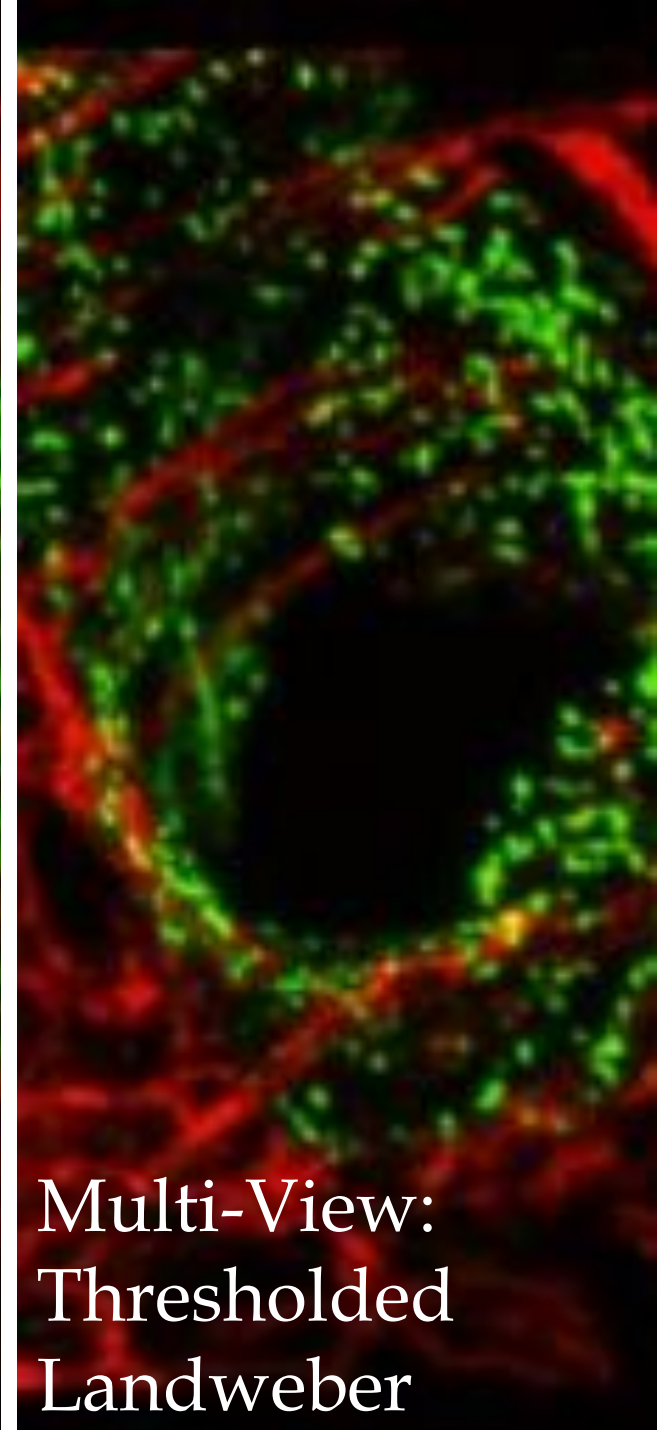
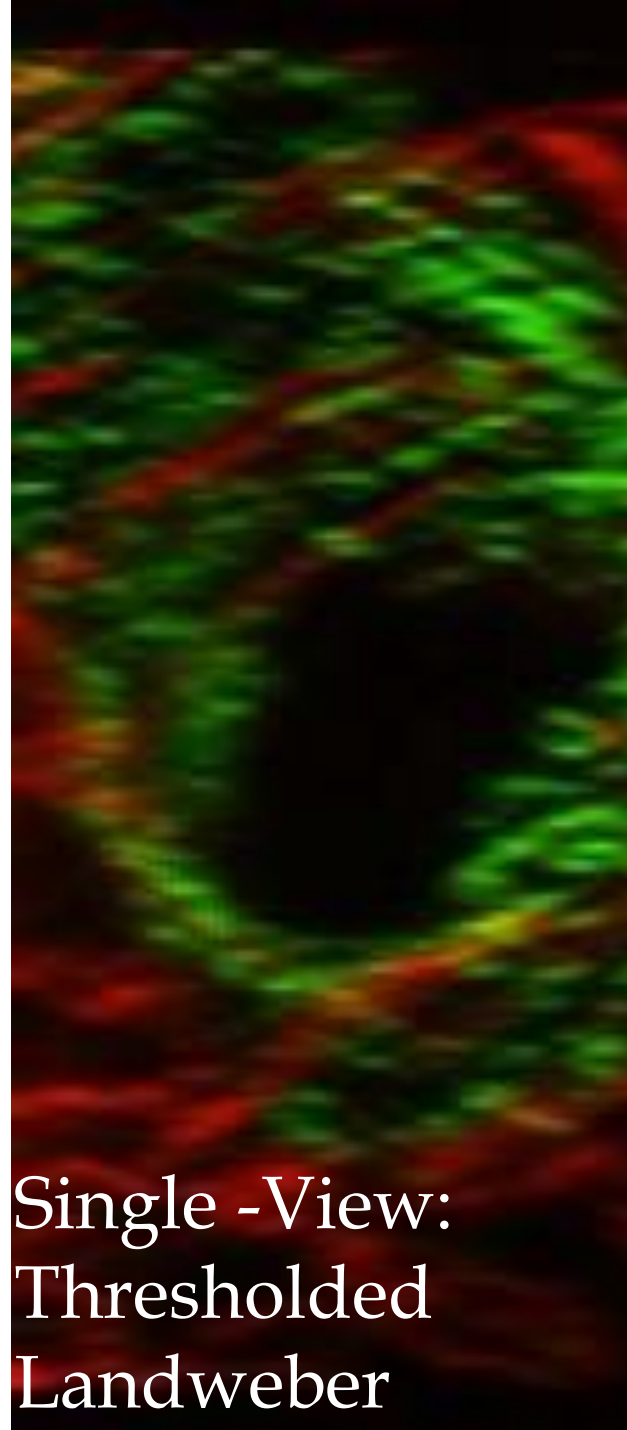
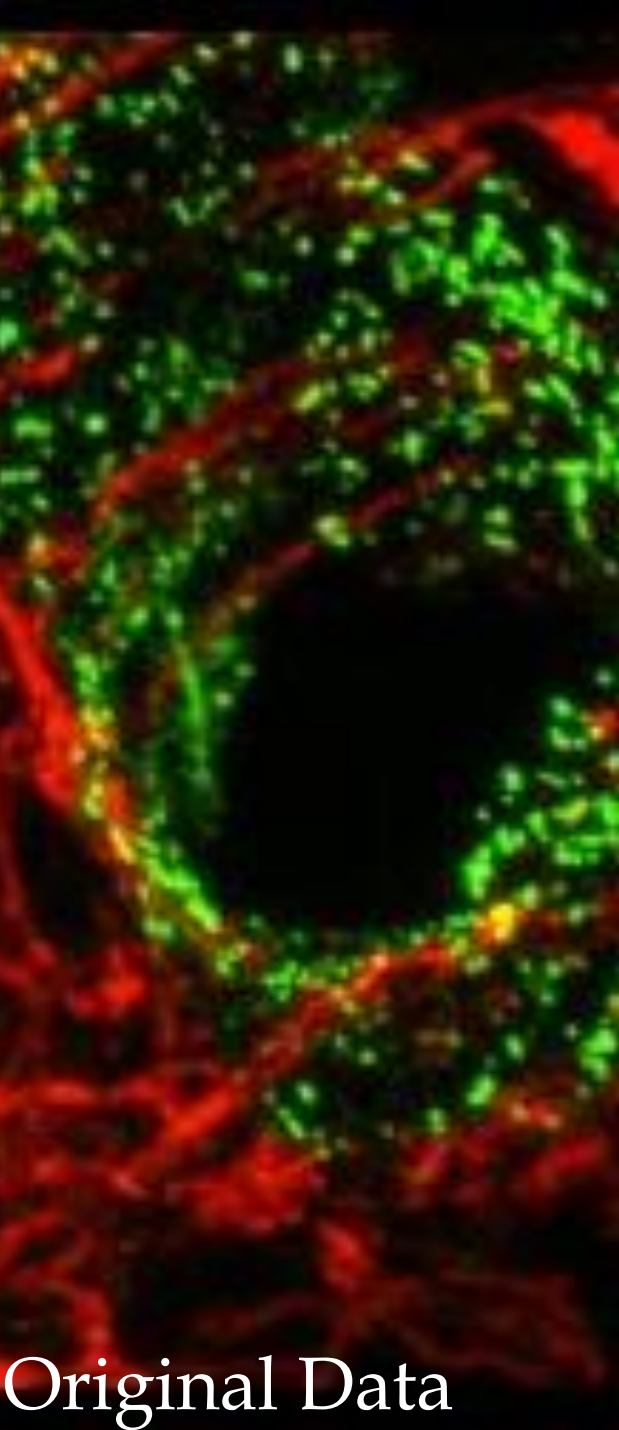
15.0 um

Angle 135  
(max. blur  
135 degrees  
from z-axis)



15.0 um





# Conclusions and Future Prospective

- (a) The theoretical PSF models generated according to the instrument and experimental parameters were close approximations to the actual measured data.
- (b) Deconvolved results using the theoretical PSF models were observed to be superior (less noisier) than that with the measured PSF.
- (c) The faithful registration of actual 3D datasets blurred along different angles still remains a problem that is unsolved, though the simulation results for the multi-angle deconvolution look promising.

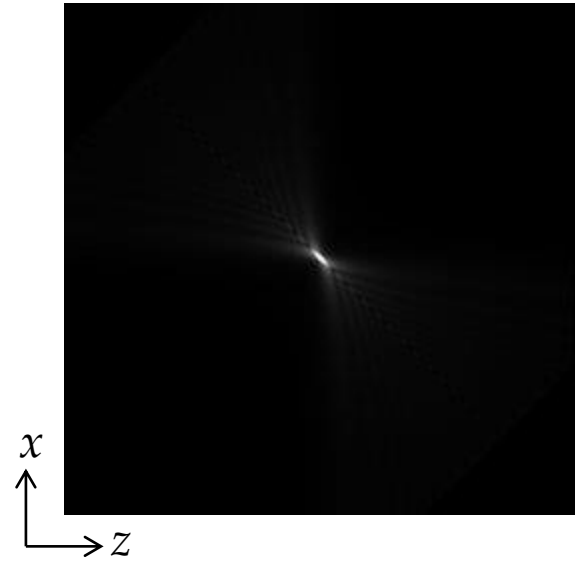
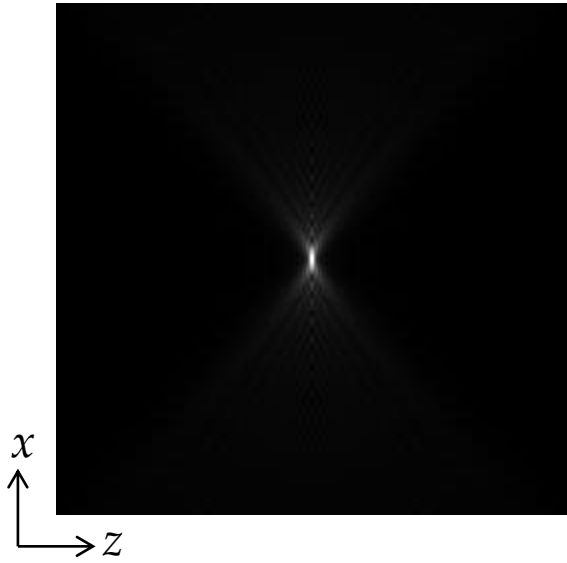
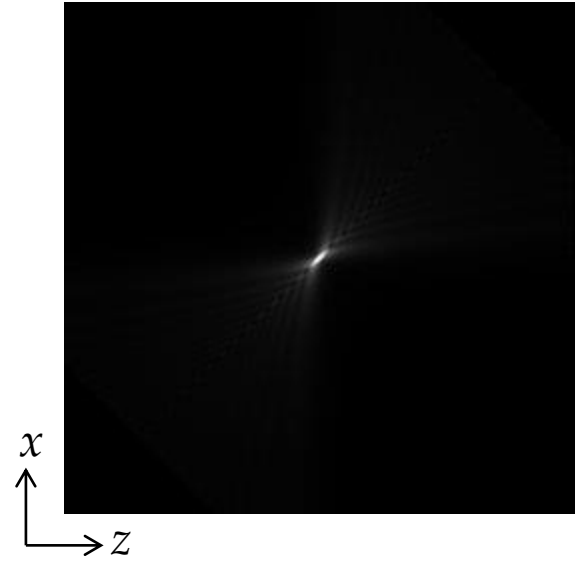
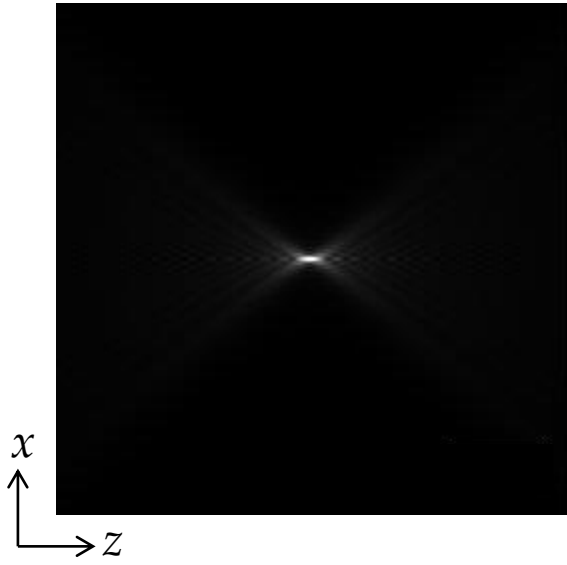
# Thank You

- INSET - Internships in Nanosystems Science, Engineering and Technology
- Systems Bioimaging Lab
  - Dr. Michael Liebling
  - Nikhil Chacko
  - Kevin Chan
  - Michael Lee

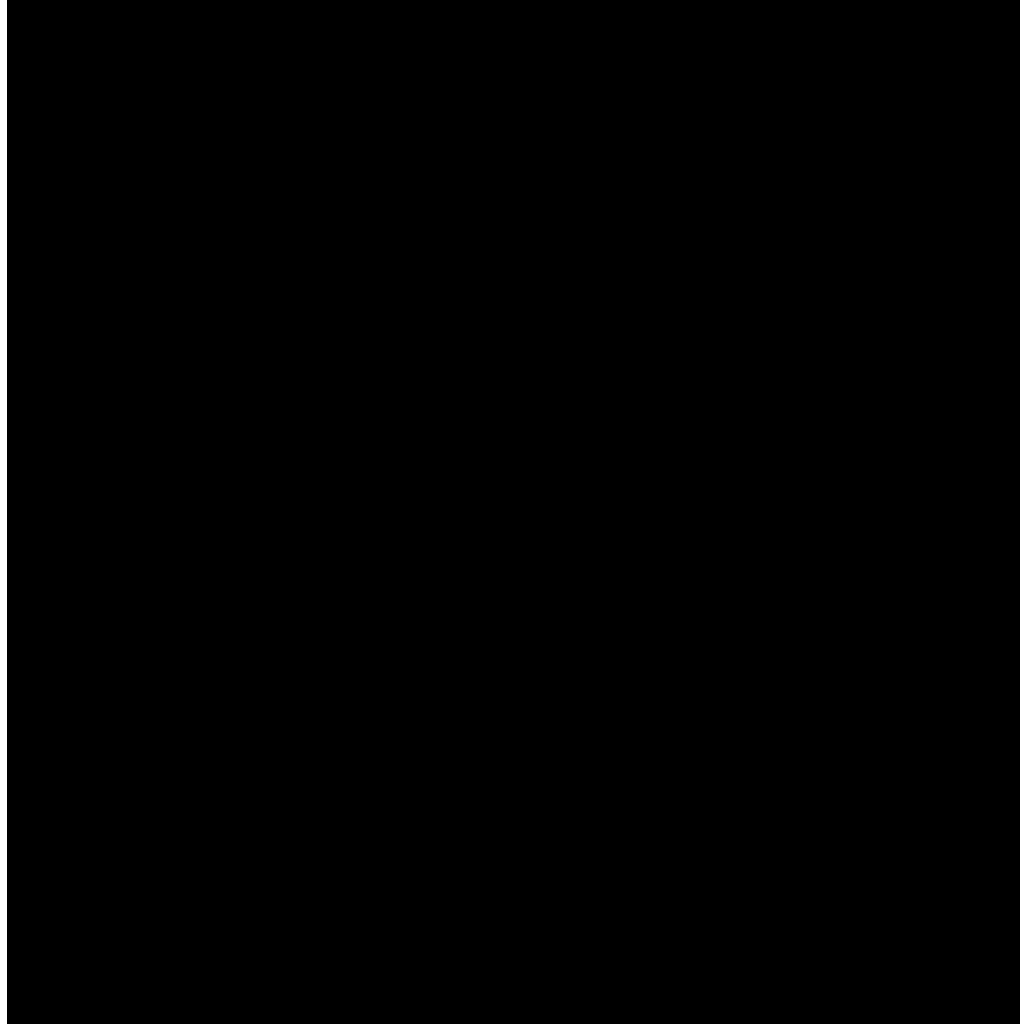


# Appendix





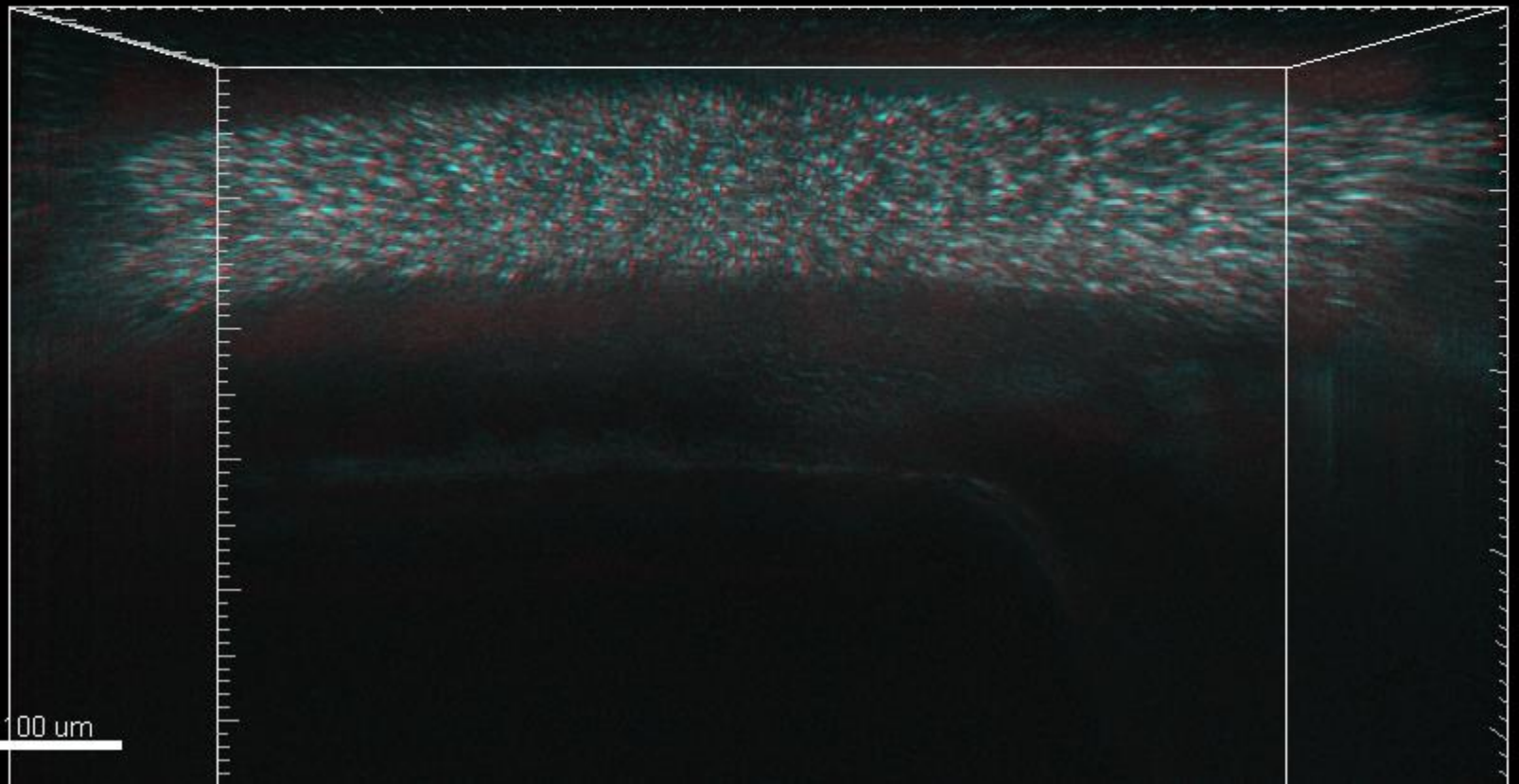
# Zebrafish - Z-Stack



# Zebrafish Single-View Deconvolution

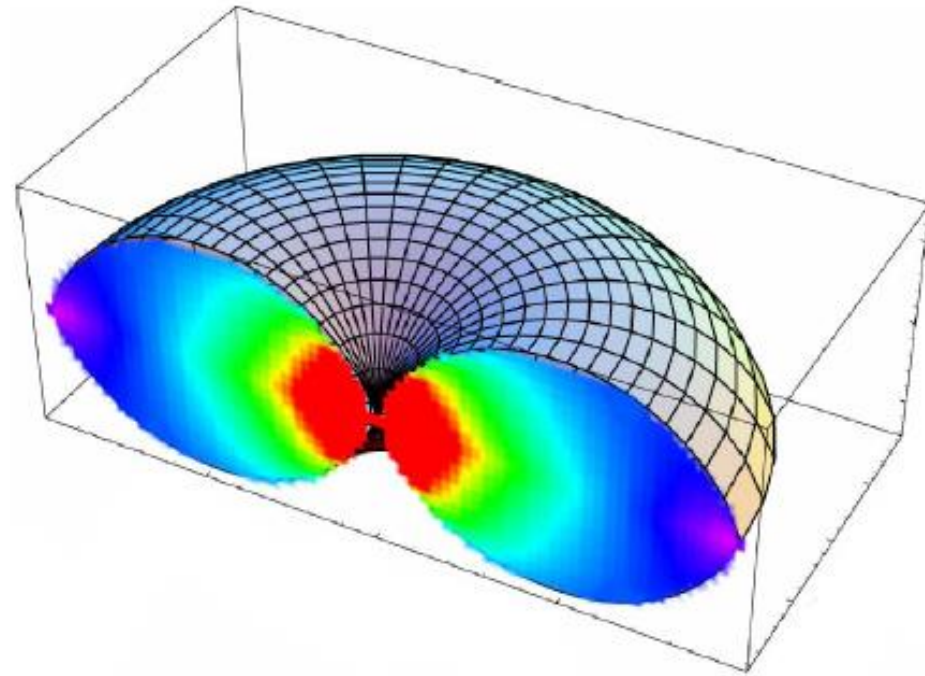
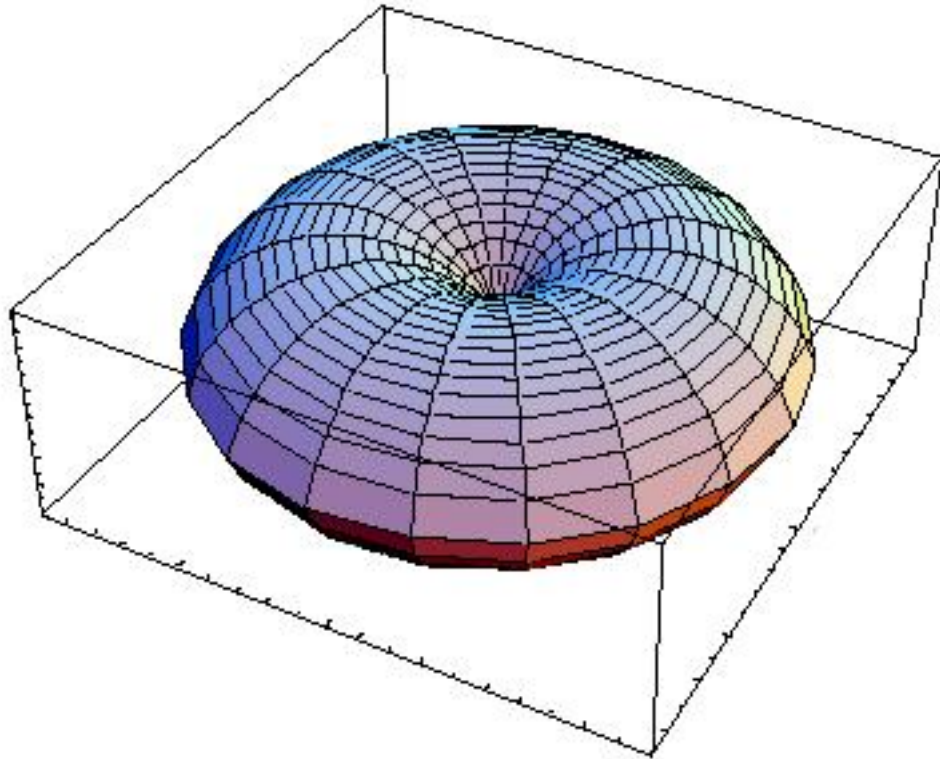
## Results

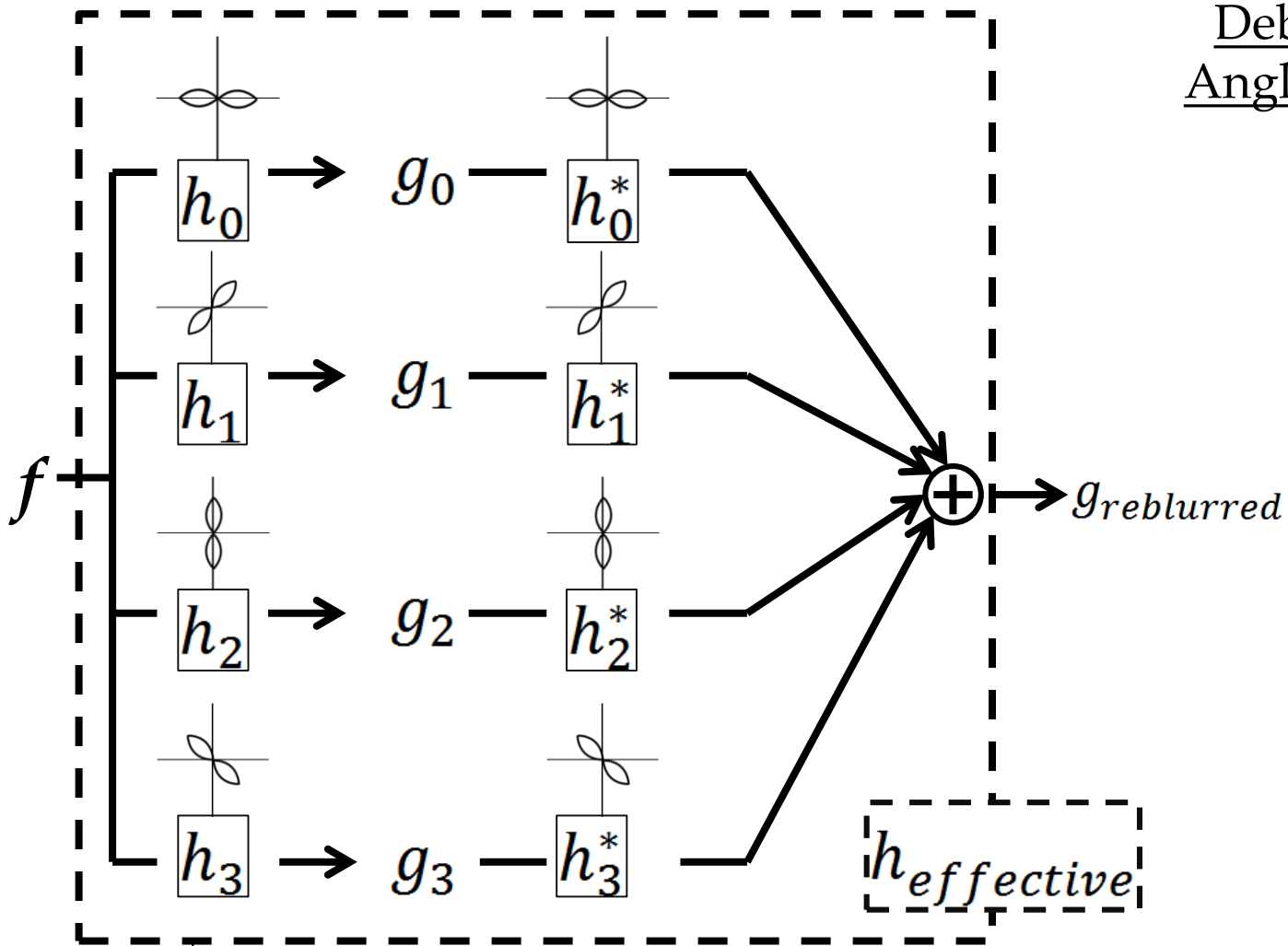
### *Measured VS Theoretical PSF*



Method	Signal Estimate	Comments
Inverse Filtering	$\tilde{f}_e = \arg \min_{\tilde{f}} \  \tilde{g} - \tilde{H} \cdot \tilde{f} \ _2^2$	<ul style="list-style-type: none"> <li>• Linear filtering operation</li> <li>• Amplifies noise when <math>H(\omega) \rightarrow 0</math></li> </ul>
Landweber	$\tilde{f}_e = \arg \min_{\tilde{f}} \  \tilde{g} - \tilde{H} \cdot \tilde{f} \ _2^2$	<ul style="list-style-type: none"> <li>• Iterative</li> <li>• Doesn't amplify noise</li> </ul>
Regularized Inverse Filtering	$f_e = \arg \min_{\tilde{f}} \  \tilde{g} - \tilde{H} \cdot \tilde{f} \ _2^2 + \lambda \  \gamma \cdot \tilde{f} \ _2^2$	<ul style="list-style-type: none"> <li>• Tries to smoothen image in addition to inverse filtering</li> </ul>
Wiener Filtering	$f_e = \arg \min E   F(\omega) - F_e(\omega)  ^2$	<ul style="list-style-type: none"> <li>• Linear filtering operation</li> <li>• Used in noisy cases</li> </ul>
Richardson-Lucy	$f_e = \arg \max$ $P(f   g) = \frac{P(g   f) \cdot P(f)}{\int P(g   f) \cdot P(f) \cdot df}$	<ul style="list-style-type: none"> <li>• Assumes that input is Poisson distributed (appropriate for photon noise in data)</li> <li>• Developed from Bayes' Theorem</li> </ul>
Thresholded Landweber (TL)	$\tilde{f}_e = \arg \min_{\tilde{f}} \  \tilde{g} - \tilde{H} \cdot \tilde{f} \ _2^2 + \lambda \  \tilde{W} \cdot \tilde{f} \ _1$	<ul style="list-style-type: none"> <li>• Assumes wavelet coefficients of the data to be estimated are sparse.</li> </ul>
Multi-Channel Thresholded Landweber	$\tilde{f}_e = \arg \min_{\tilde{f}} \sum_{i=0}^{M-1} \  \tilde{g}_i - \tilde{H}_i \cdot \tilde{f} \ _2^2 + \lambda \  \tilde{W} \cdot \tilde{f} \ _1$	<ul style="list-style-type: none"> <li>• Extension of TL to multi-channel framework.</li> </ul>

# PSF- Fourier Transform Representation





$f \xrightarrow{h_{effective}} g_{reblurred}$

$$C(f) = \sum_{i=0}^3 \|g_i - H_i \cdot f\|_2^2 + \lambda \|W \cdot f\|_1^1$$