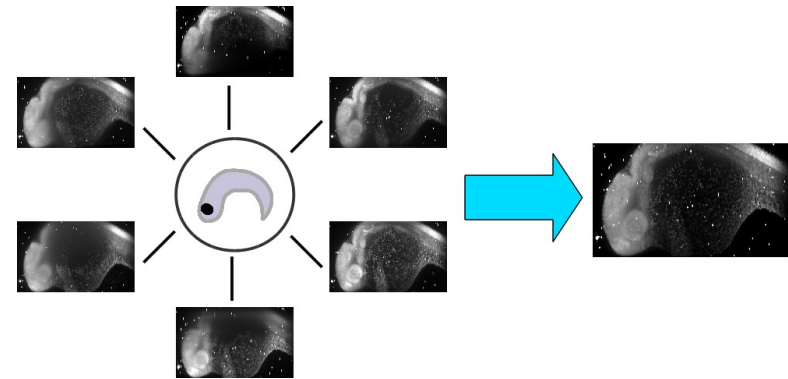


# SPATIALLY-VARIANT LUCY-RICHARDSON DECONVOLUTION FOR MULTIVIEW FUSION OF MICROSCOPICAL 3D IMAGES

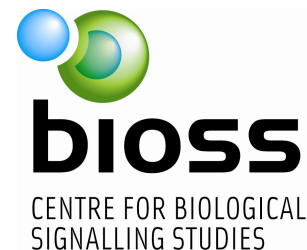
Maja Temerinac-Ott

Olaf Ronneberger, Roland Nitschke,

Wolfgang Driever and Hans Burkhardt



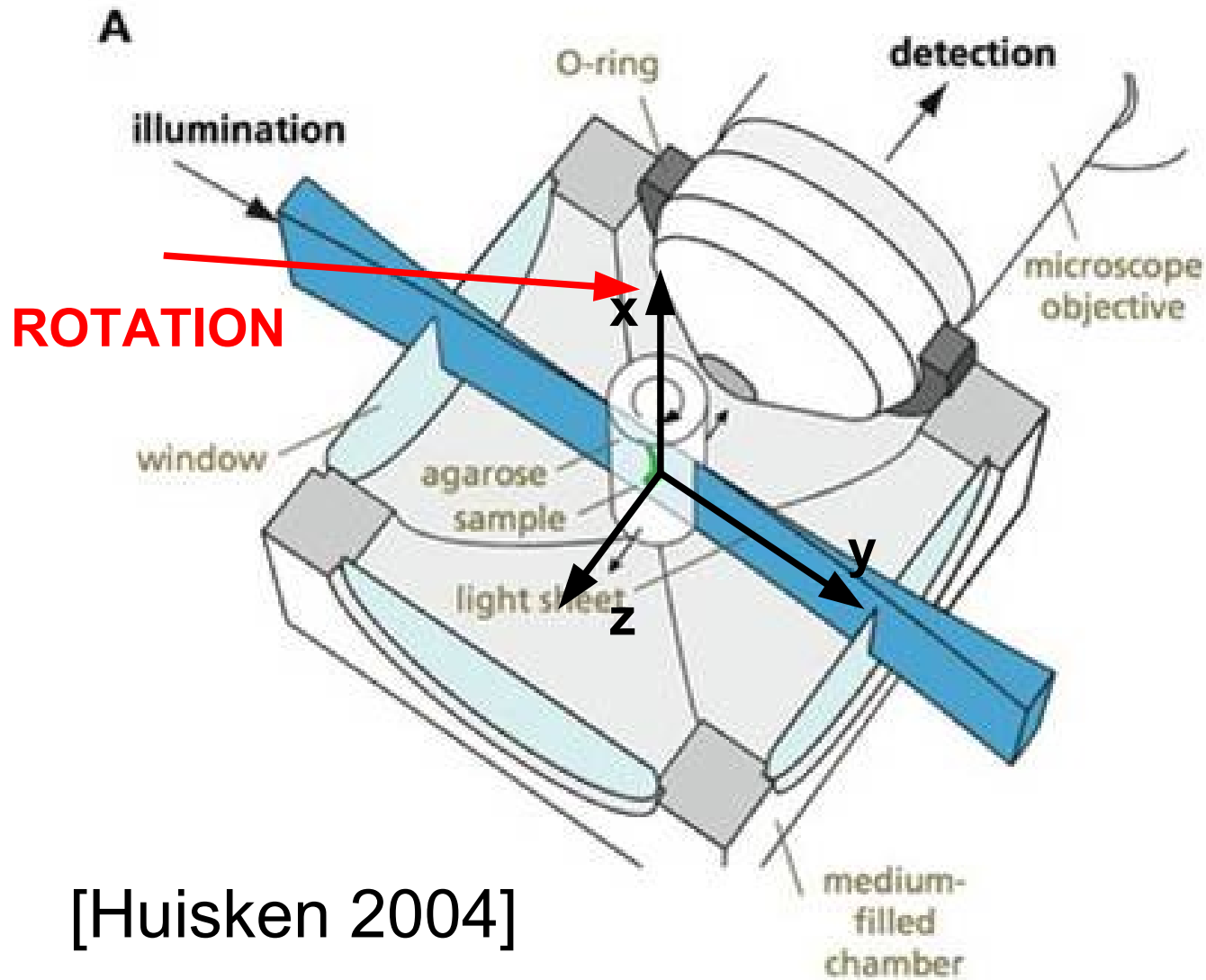
University of Freiburg, Germany



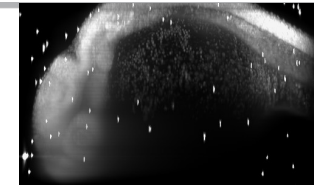
UNI  
FREIBURG

The Third LSM Workshop, Toulouse, October 13<sup>th</sup>-14<sup>th</sup>, 2011

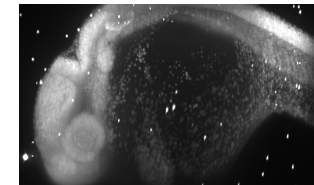
# SPIM = Single Plane Illumination Microscopy



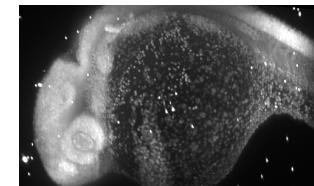
[Huisken 2004]



view 0°



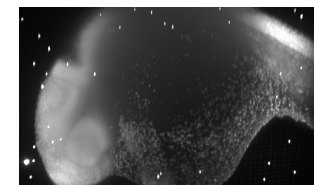
view 60°



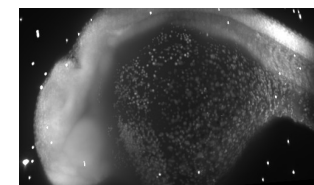
view 120°



view 180°

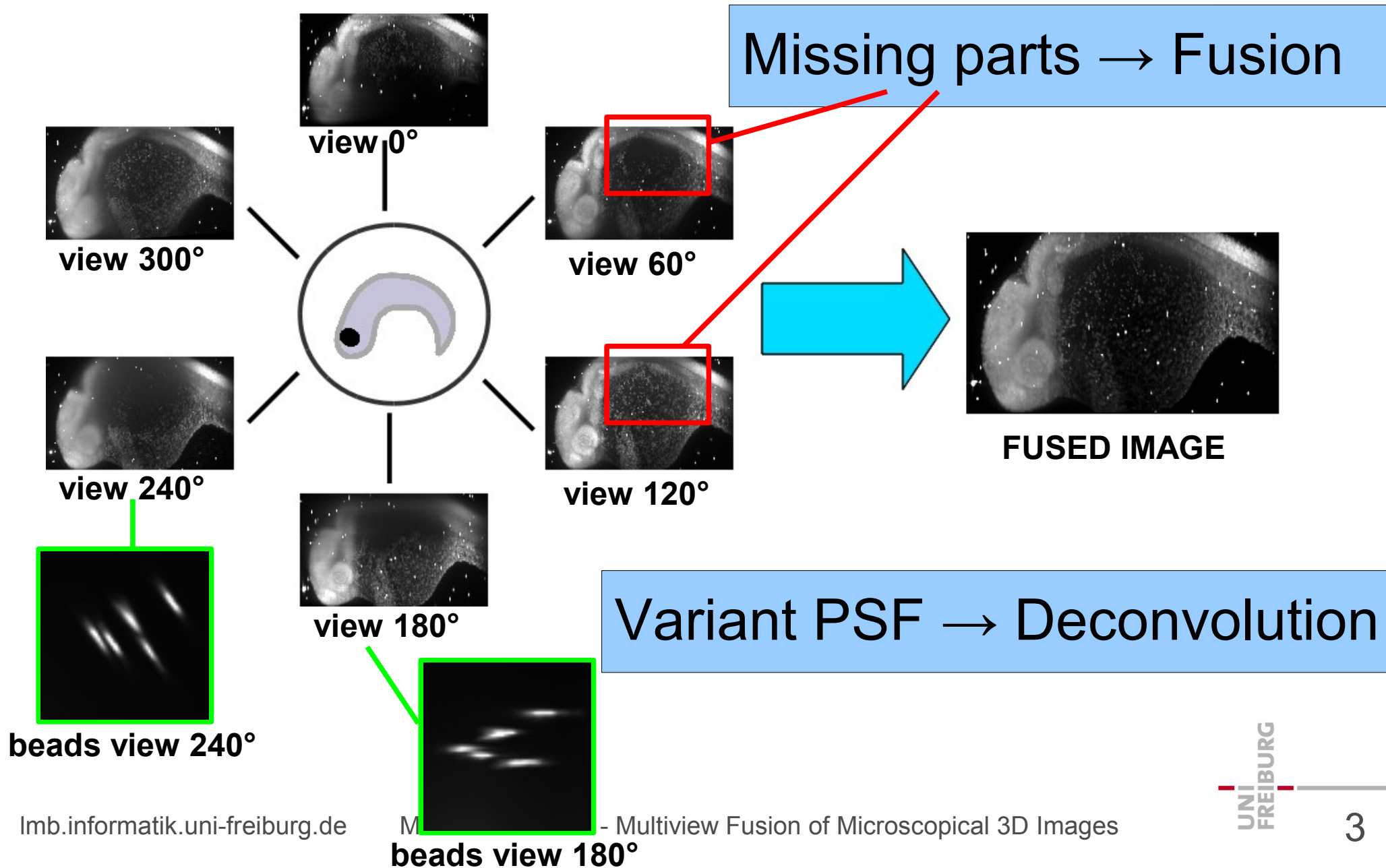


view 240°

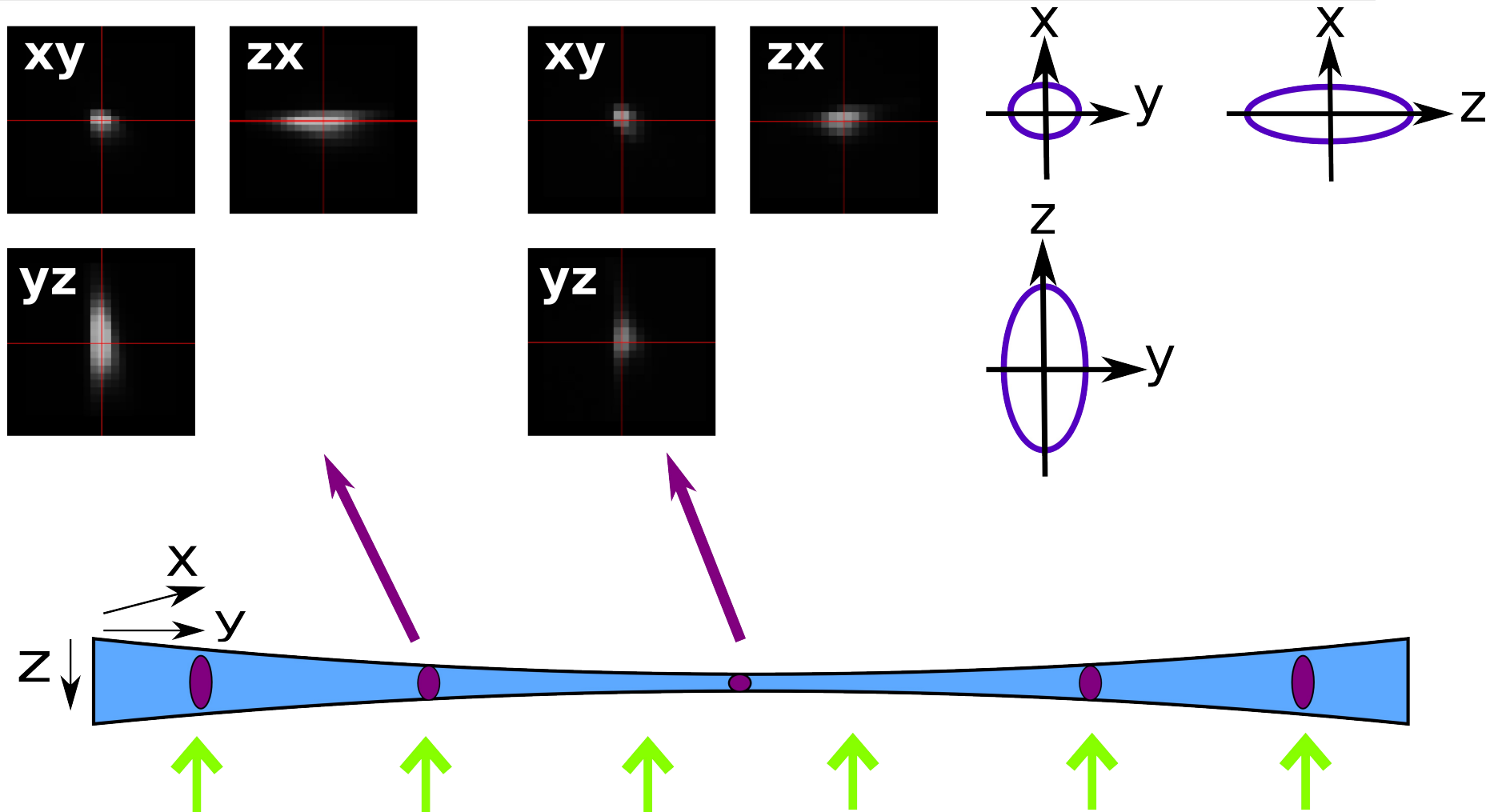


view 300°

# Goal: Joint Fusion and Deconvolution



# Estimation of the PSF at Bead Positions



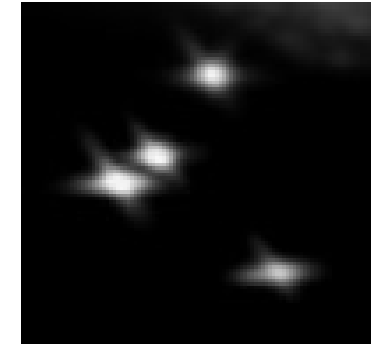
➤ Variation of the PSF along  $y$ -axis

# Related Work

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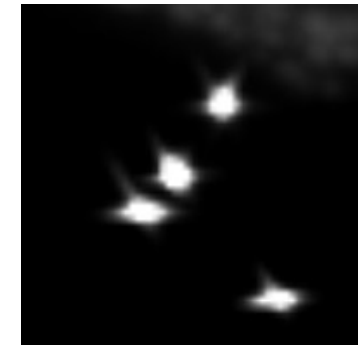
- Blending [Preibisch 2010]

- Combines Gray values without a prior model
  - Fast Computation
  - Smearing of the points + blur



- Average PSF for Multiview Deconvolution [Krzic 2009]

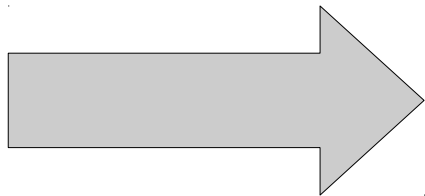
- Assumes constant PSF
  - Good in the center
  - Bad at the corners of the image



# Contribution

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- Location **variant PSF estimation** for joint deconvolution and fusion
- Approach:
  - PSF Estimation
  - Overlap-Save Deconvolution
  - Lucy-Richardson Algorithm
  - Multiview deconvolution
  - TV Regularization



**LRMOS-TV**

# Problem Formulation: Multiview Fusion

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## ➤ **Given:**

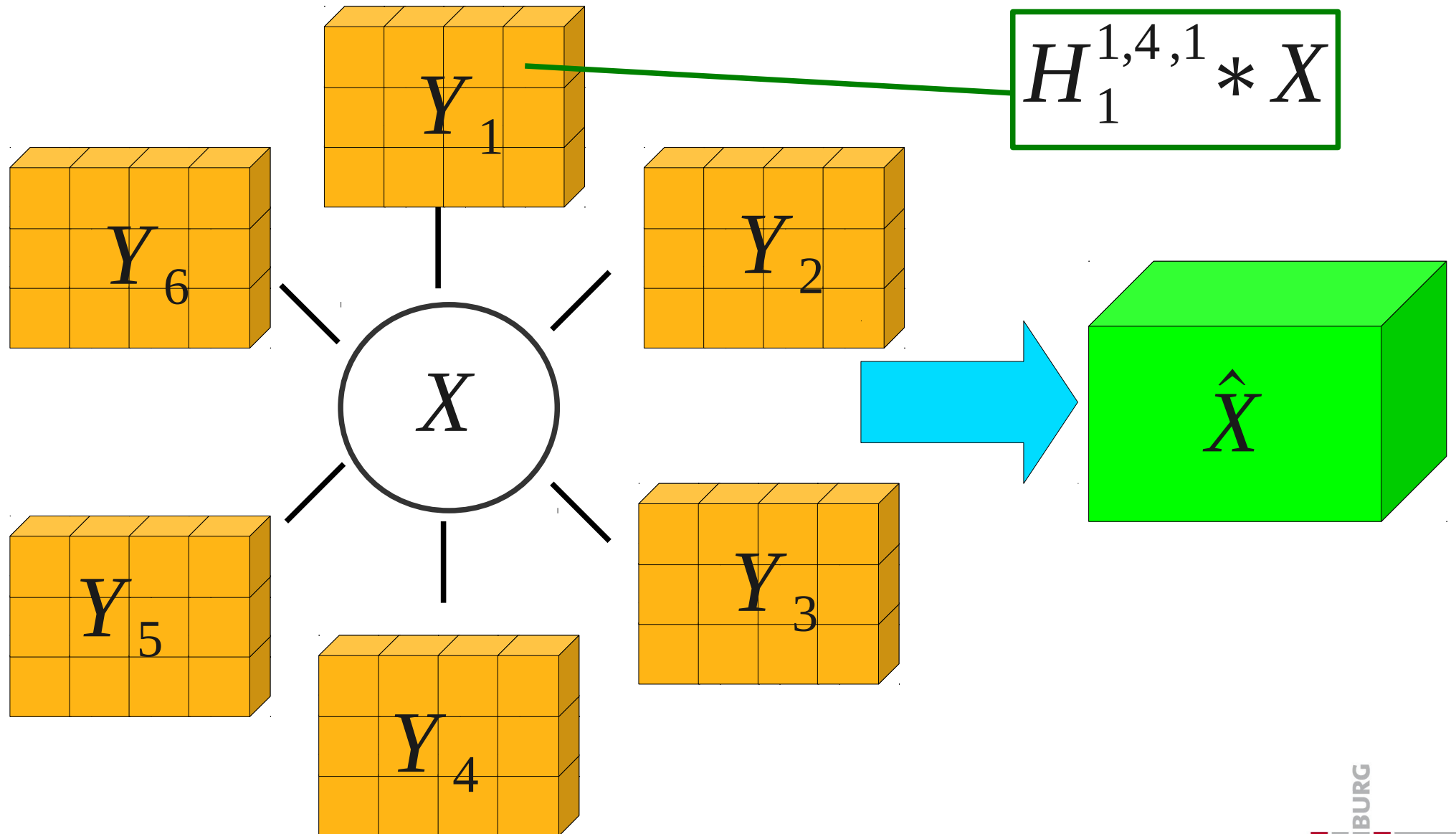
- **Recorded images**  $Y_1, \dots, Y_N$
- **PSF at bead positions**  $H_1, \dots, H_N$

## ➤ **Goal:**

- **Find true image**  $X$   
that maximizes

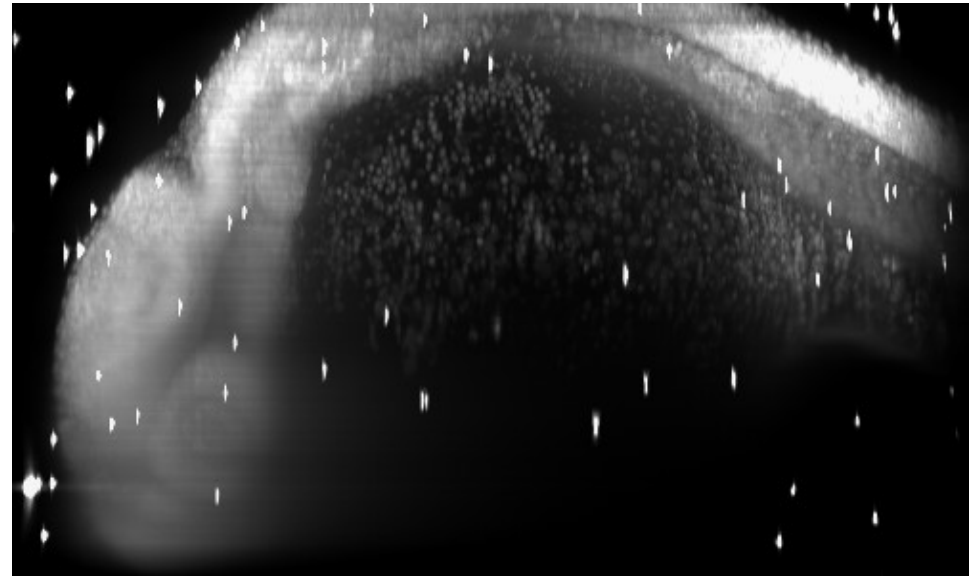
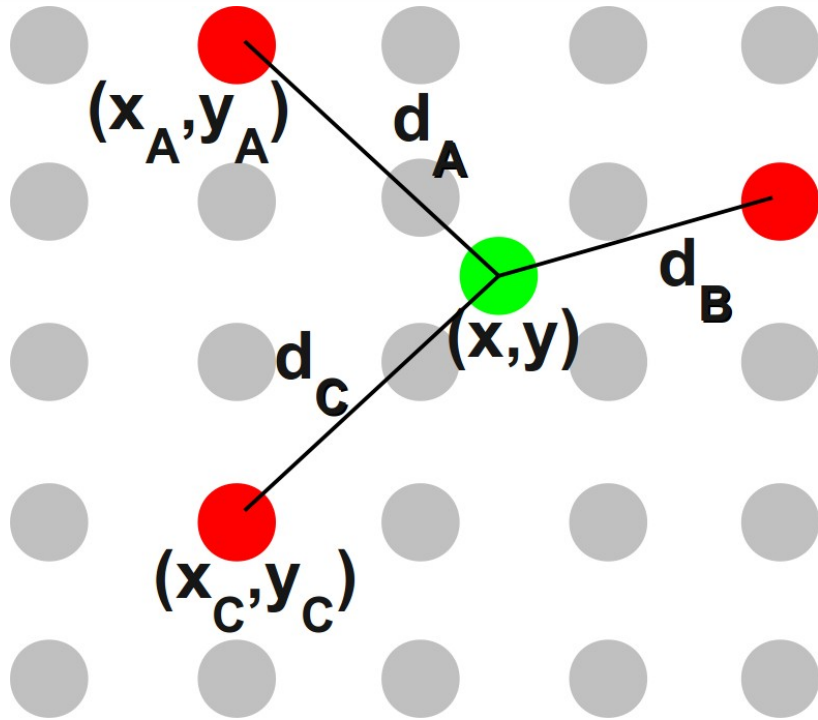
$$p(X | Y_1, \dots, Y_N, H_1, \dots, H_N) = \prod_{i=1}^N p(X | Y_i)$$

# Solution: Regionwise Multiview Fusion





# PSF Estimation



$$H(x, y) = \frac{d_B d_C H_A + d_A d_C H_B + d_A d_B H_C}{d_B d_C + d_A d_C + d_A d_B}$$

$$d_A = \sqrt{(x - x_A)^2 + (y - y_A)^2}$$

# Overlap-Save Deconvolution

- Model spatially-variant PSF by blockwise constant PSFs
- Consider large overlapping regions to overcome boundary artifacts

$$\begin{bmatrix} Y_{11} & Y_{12} & \dots & Y_{1n} \\ Y_{21} & Y_{22} & \dots & Y_{2n} \\ \vdots & \vdots & & \vdots \\ Y_{n1} & Y_{n2} & \dots & Y_{nn} \end{bmatrix} \rightarrow Y_{ij}^{(r+s)} = \begin{bmatrix} \times & \times & \times \\ \times & Y_{ij} & \times \\ \times & \times & \times \end{bmatrix}$$

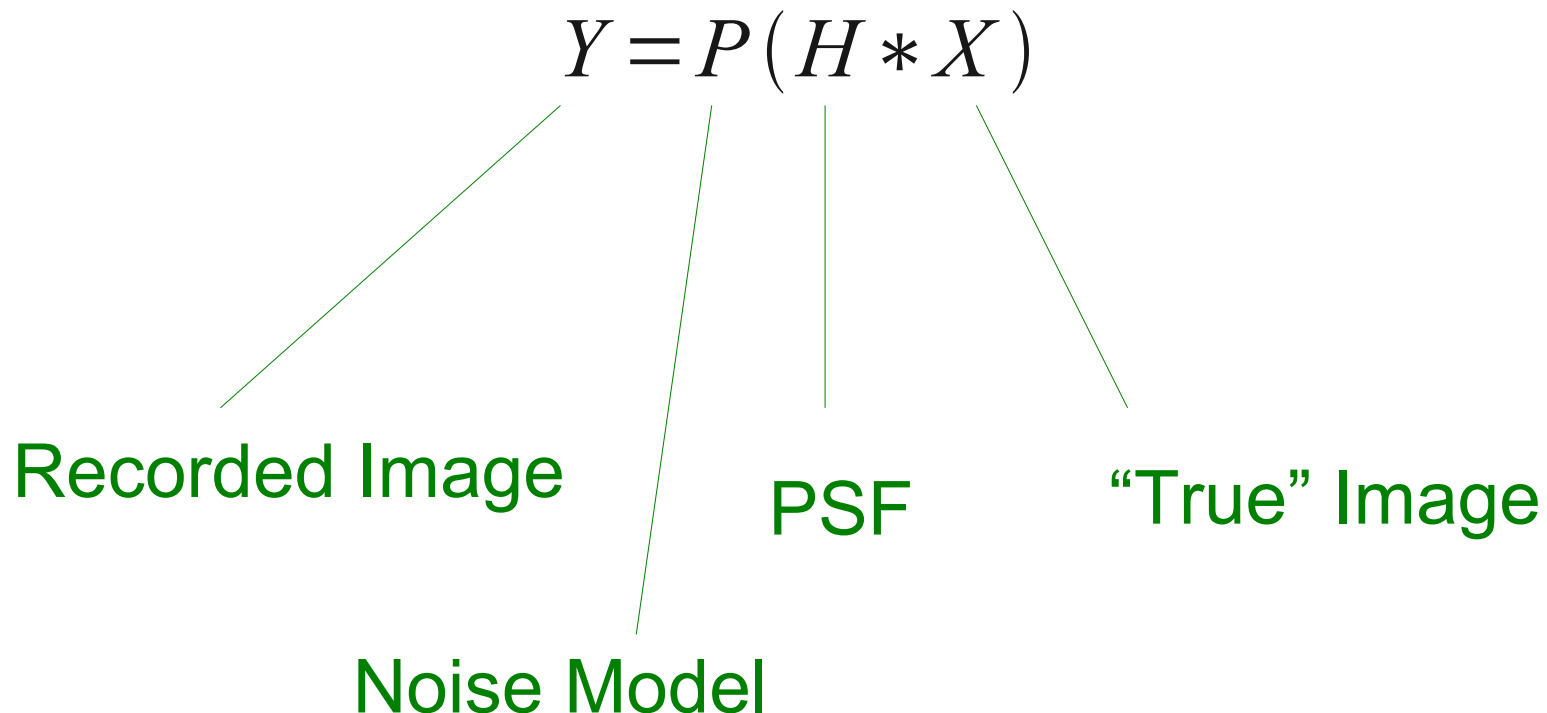
Size of the blocks:  
 $s \times s$

Size of the padded blocks:  
 $(s+r) \times (s+r)$

# Image Formation Model

---

- Convolution with the PSF of the system:

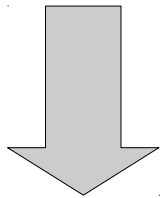


# Deconvolution: MLE Estimation

- Image Statistics Modeled by Poisson Process [Herbert 1989]:

$$p(X|Y) = \prod_{\mathbf{v}} \frac{[(H * X)(\mathbf{v})]^{Y(\mathbf{v})} \exp(-(H * X)(\mathbf{v}))}{Y(\mathbf{v})!}$$

Likelihood Probability



$$J(X) = \int_{\mathbf{v}} Y(\mathbf{v}) \log[(H * X)(\mathbf{v})] - (H * X)(\mathbf{v}) d\mathbf{v}$$

log likelihood

# Lucy-Richardson Algorithm

$$\hat{X}^{p+1}(\mathbf{v}) = \hat{X}^p(\mathbf{v}) \cdot C^p(\mathbf{v})$$

Correction Factor:

$$C^p(\mathbf{v}) = \left( H^s * \frac{Y}{S^p} \right)(\mathbf{v})$$

Simulated Image

$$H^s(\mathbf{v}) = H(-\mathbf{v})$$

$$S^p = (H * \hat{X}^p)(\mathbf{v})$$

# Multiview Deconvolution

---

- Total Correction Factor (CF) as average of the individual correction factors [Krzic 2009]:

$$C^p = \frac{1}{N} \sum_{i=1}^N C_i^p$$

- Computation of the individual CF:

$$C_i^p(\mathbf{v}) = \left( H_i^s * \frac{Y_i}{S_i^p} \right)(\mathbf{v})$$

$$S_i^p = \left( H_i * \hat{X}^p \right)(\mathbf{v})$$

# TV Regularization

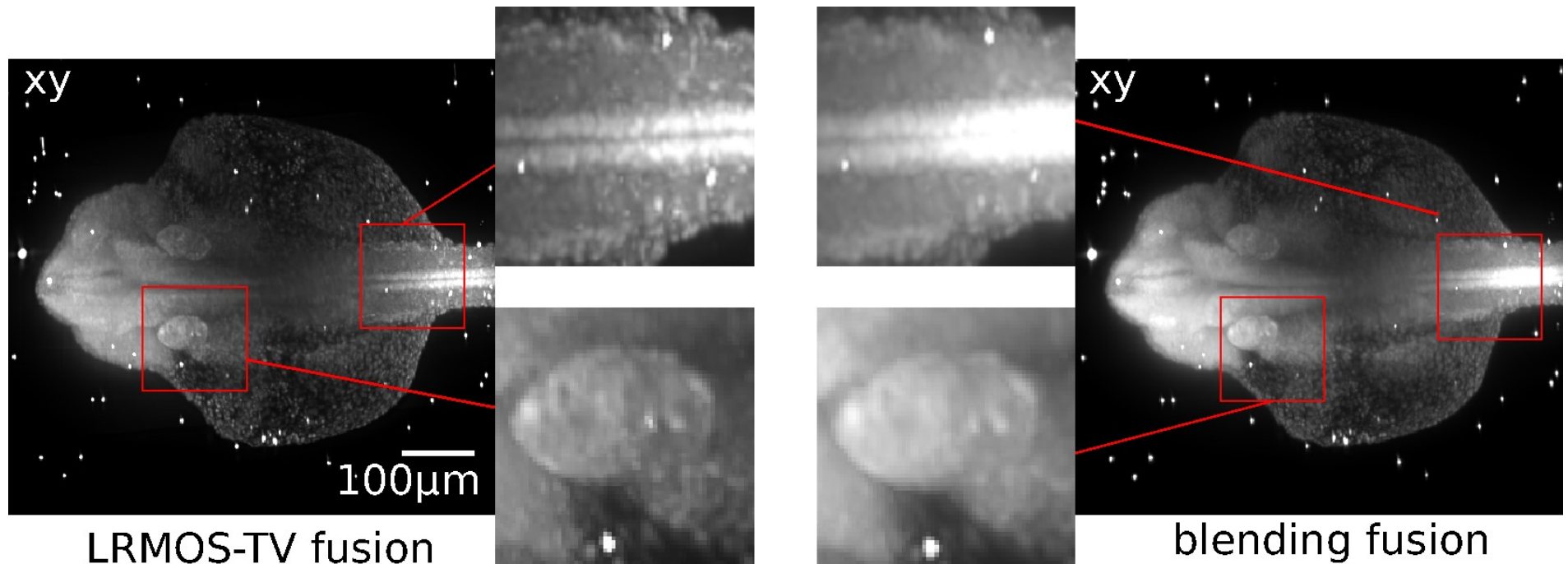
- Regularization of the initial energy by Total Variation [Dey 2004] :

$$J_{TV}(X) = J(X) + \lambda \int_{\mathbf{v}} |\nabla X(\mathbf{v})| d\mathbf{v}$$

- Resulting iteration using Green's one-step-late (OSL) algorithm:

$$\hat{X}^{p+1}(\mathbf{v}) = \frac{\hat{X}^p(\mathbf{v})}{1 - \lambda \operatorname{div} \left( \frac{\nabla (\hat{X}^p(\mathbf{v}))}{|\nabla (\hat{X}^p(\mathbf{v}))|} \right)} \cdot C^p(\mathbf{v})$$

# Results: Visual Comparison to Blending



Parameters:

$r = 11$ ,  $p = 4$ ,

$s+r = 64$

Computation Time: 40 min

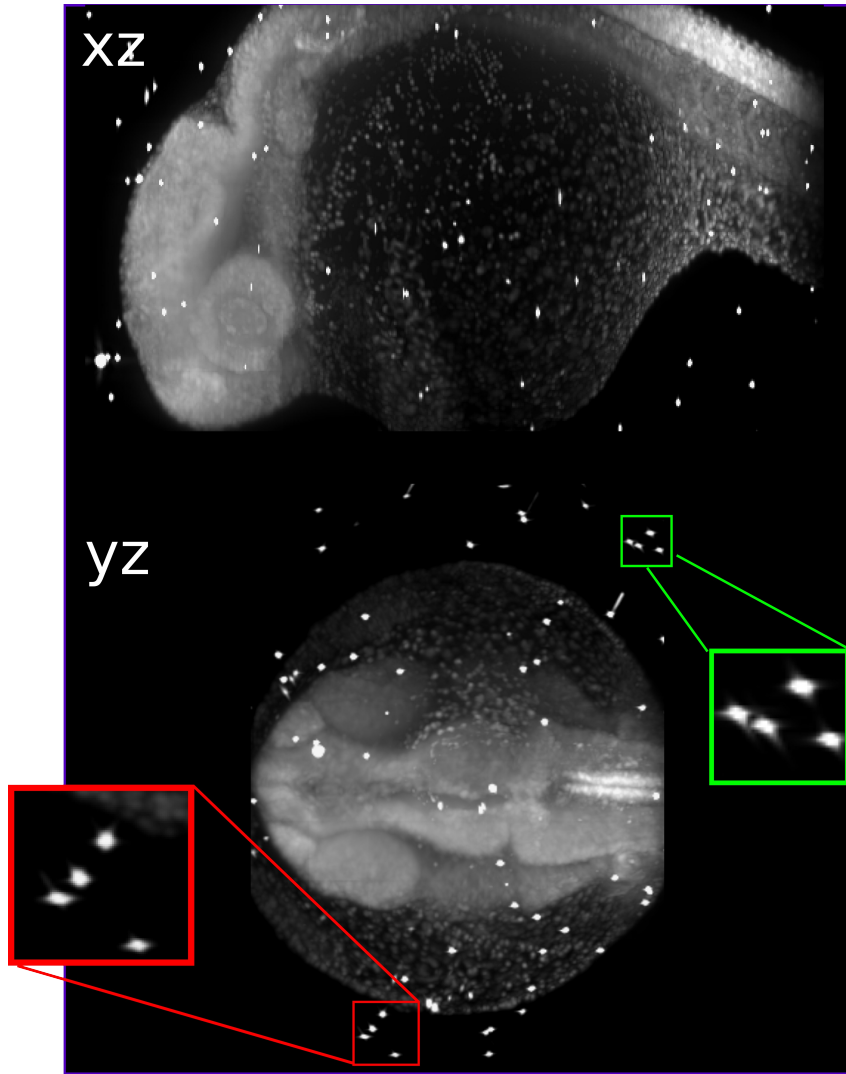
[Preibisch 2010]

Computation Time: 20 min

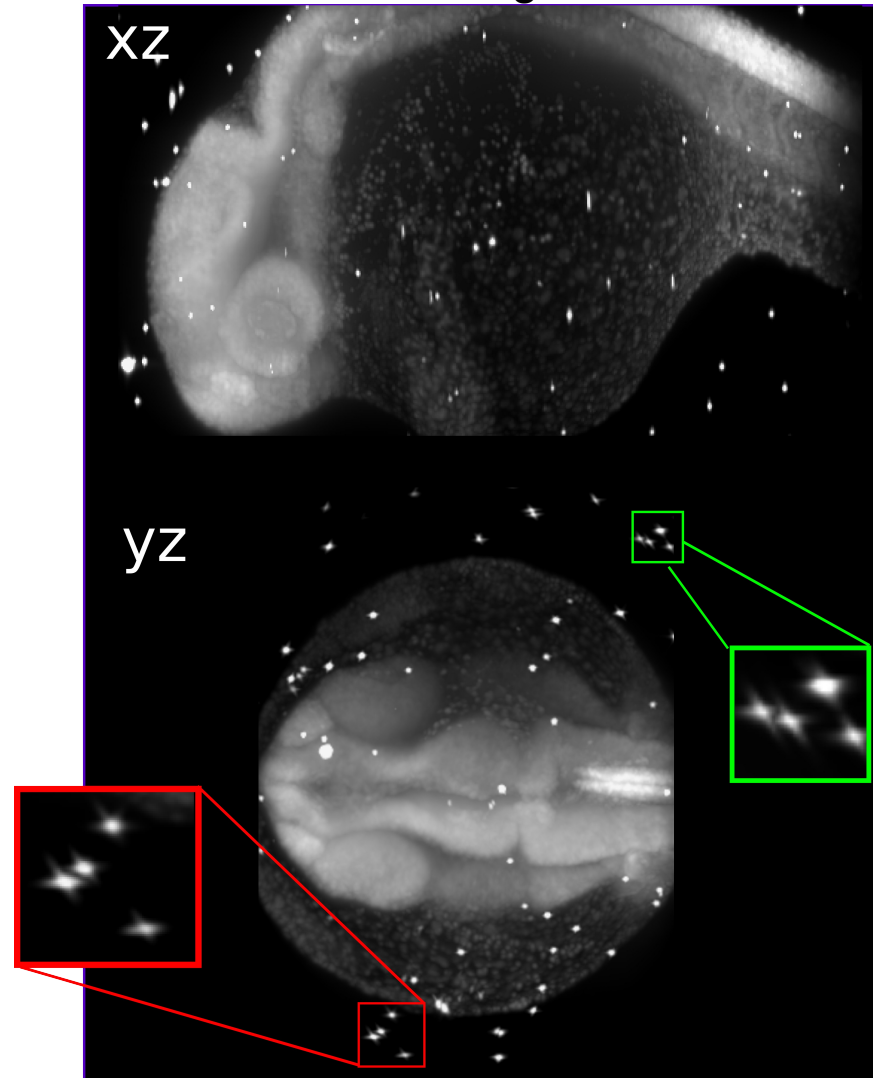


# Results: Visual Comparison to Blending

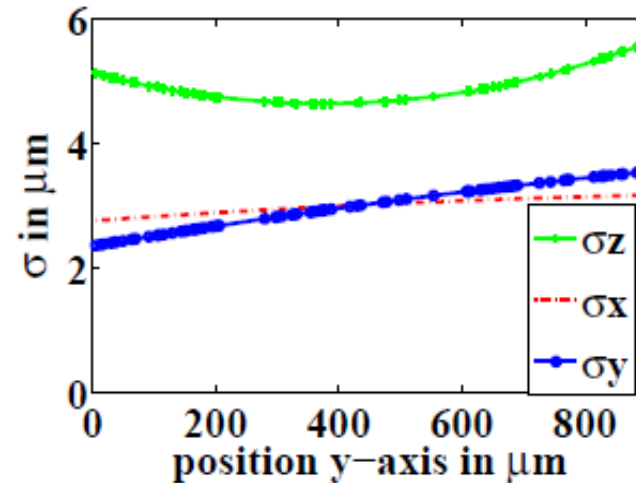
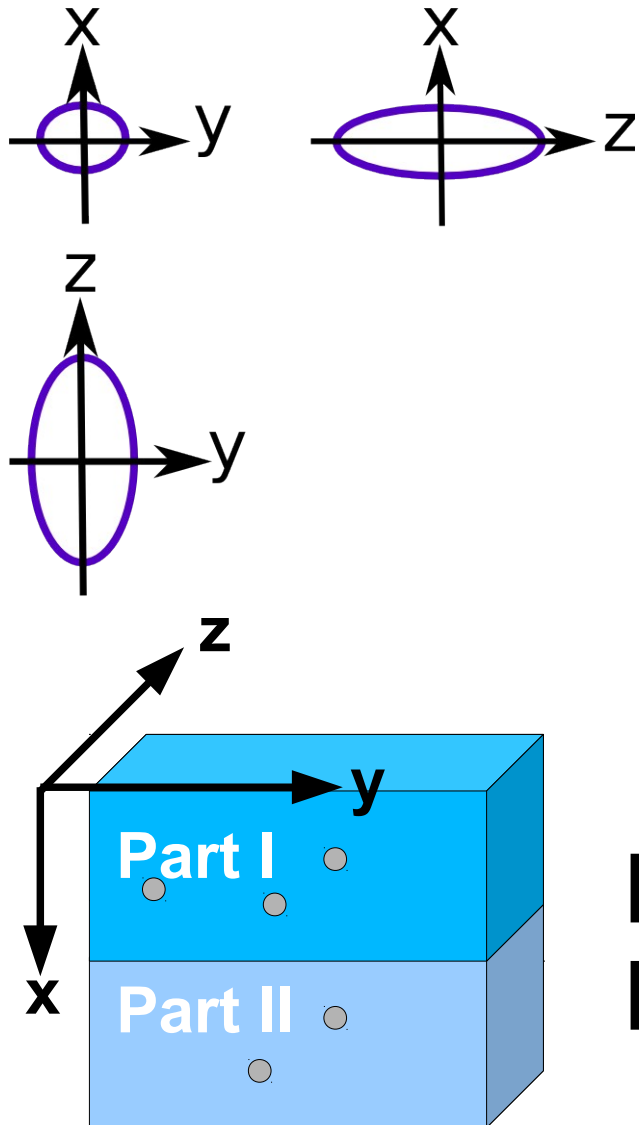
LRMOS-TV fusion



Blending fusion



# Quantitative Evaluation

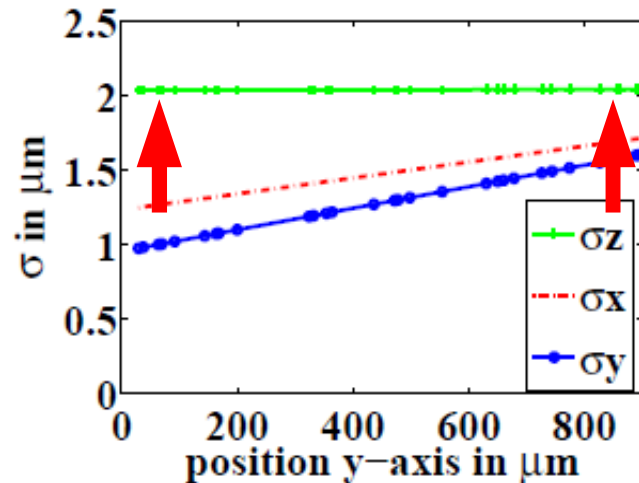
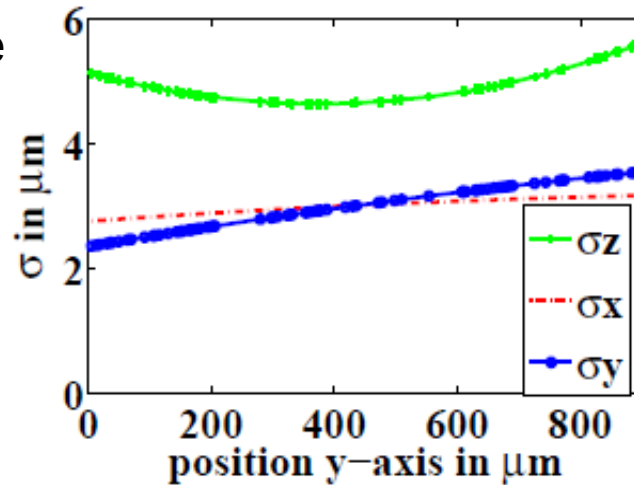


Original bead shape  
(single view)

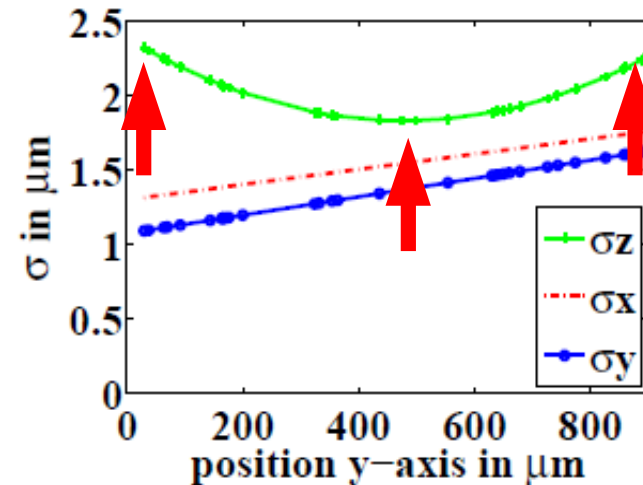
Part I: PSF Estimation  
Part II: Multiview Fusion

# Results: Comparison to Average PSF

Original bead shape  
(single view)

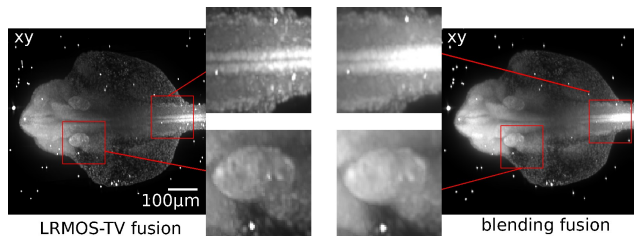
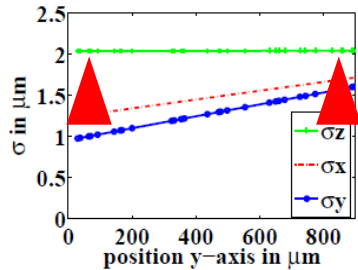
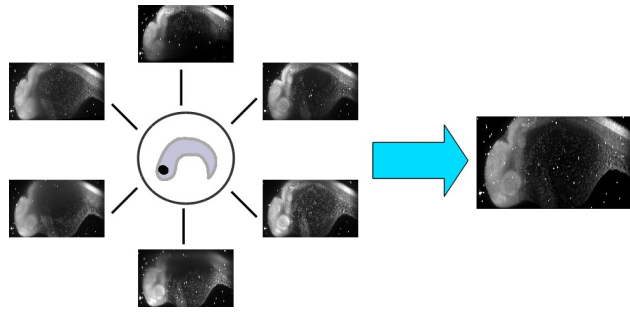


Deconvolved with variant PSF  
(fused image, upper)



Deconvolved with average PSF  
(fused image, upper)

# Conclusions



- A **new framework** for the fusion of the SPIM images was presented
- Spatially-variant Deconvolution **better models the optical properties** of the system than existing methods
- The structure **borders are well preserved** due to the TV regularization
- The algorithm is **fast** and can be **easily parallelized**

$$\begin{bmatrix} Y_{11} & Y_{12} & \dots & Y_{1n} \\ Y_{21} & Y_{22} & \dots & Y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ Y_{n1} & Y_{n2} & \dots & Y_{nn} \end{bmatrix} \rightarrow Y_{ij}^{(r+s)} = \begin{bmatrix} \times & \times & \times \\ \times & Y_{ij} & \times \\ \times & \times & \times \end{bmatrix}$$

---

Thank you for your attention!

# Proposed Algorithm ("LRMOS-TV")

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**for**  $m = 1$  to  $T_1$  **do**  
  **for**  $n = 1$  to  $T_2$  **do**  
    **for**  $k = 1$  to  $T_3$  **do**  
      1. Extract extended region  $R_i = Y_{mnk}^{(r+s)}$   
      from  $Y_i$  for each view  $i$ .  
      2. Obtain  $H_i = H_{m,n,k}^{(r+s)}$   
      by padding with zeros for each view  $i$ .  
      3. Compute the initial estimate:  
       $\hat{X}^0 = \frac{1}{N} \sum_{i=1}^N R_i^p$   
      4. Iterate:  
      
$$\hat{X}_{m,n,k}^{p+1}(\mathbf{v}) = \frac{\hat{X}_{m,n,k}^p(\mathbf{v})}{1 - \lambda \operatorname{div} \left( \frac{\nabla \hat{X}_{m,n,k}^p(\mathbf{v})}{|\nabla \hat{X}_{m,n,k}^p(\mathbf{v})|} \right)} \cdot C^p(\mathbf{v})$$
  
      5. Extract  $\hat{X}_{mnk}$  from  $\hat{X}_{mnk}^{(r+s)}$  and save into  $\hat{X}$ .  
    **end for**  
  **end for**  
**end for**

# Outlook

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- **Algorithm:**

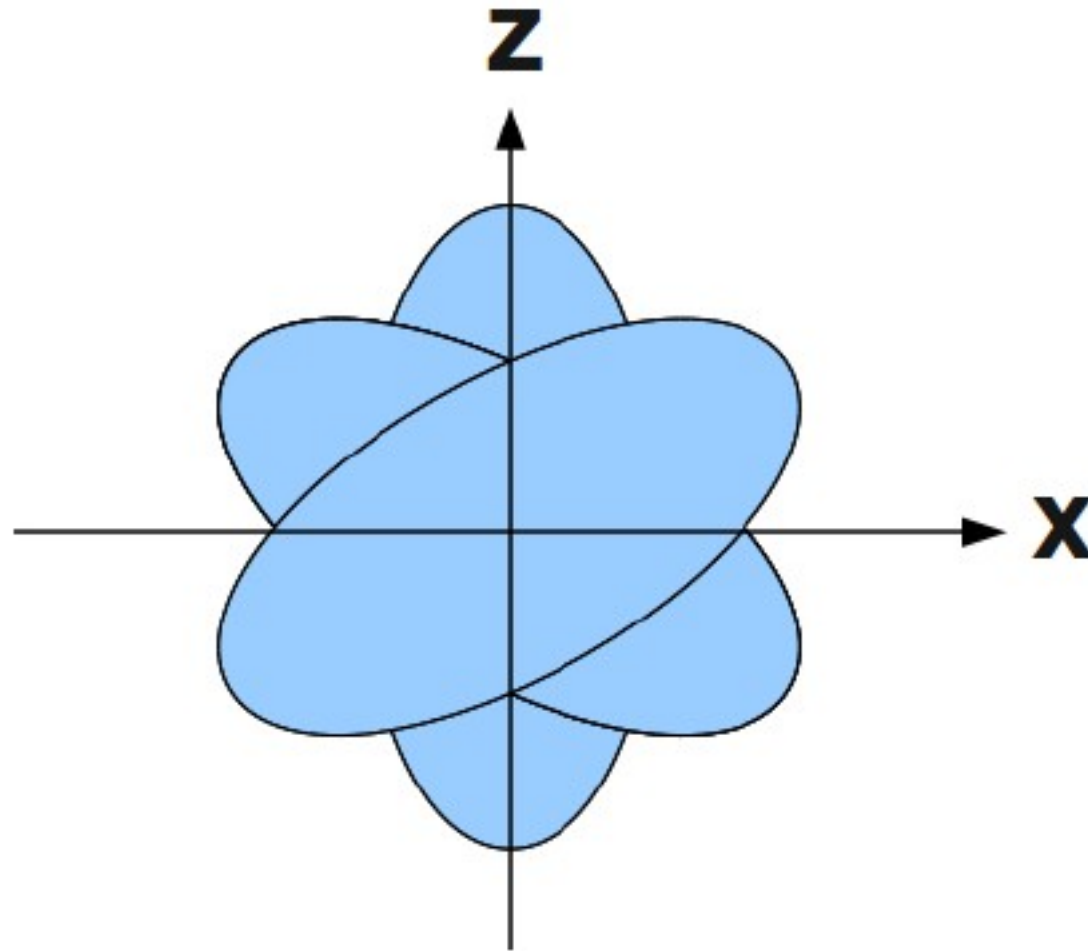
- Additional regularization strategies
- Optimal number of iteration steps
- A parametric model of the PSF along the lightsheet

- **Microscopy:**

- Insert and record beads inside the sample for better PSF modeling inside the tissue
- Automatic centering of the sample

# Coverage of the Beads in xz

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# Average PSF vs Variant PSF

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	deconvolved with average PSF	deconvolved with variant PSF
$\sigma_x$	1.5375 (max 1.6409)	1.4835 (max 1.6179)
$\sigma_y$	1.3598 (max 1.7707)	1.2937 (max 1.7233)
$\sigma_z$	2.0252 (max 2.4188)	2.0354 (max 2.038)