MAGIS-100

Ideas for 3D Image Reconstruction

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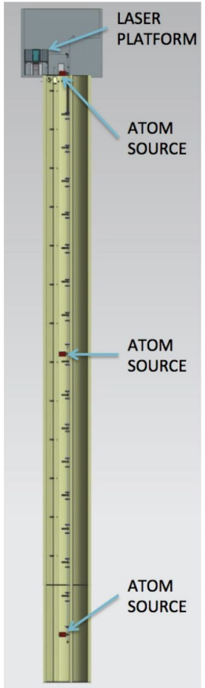
Proposal

- ❖ Advanced imaging of the clouds along the various monitoring windows of the experiment
  - ➢ Calibration / Monitoring images could be used to complement physics measurements
- ❖ Incorporate optical systems for metrology
- ❖ Leverage computational imaging techniques to gain new insights
  - ➢ 3D Imaging from 2D projections

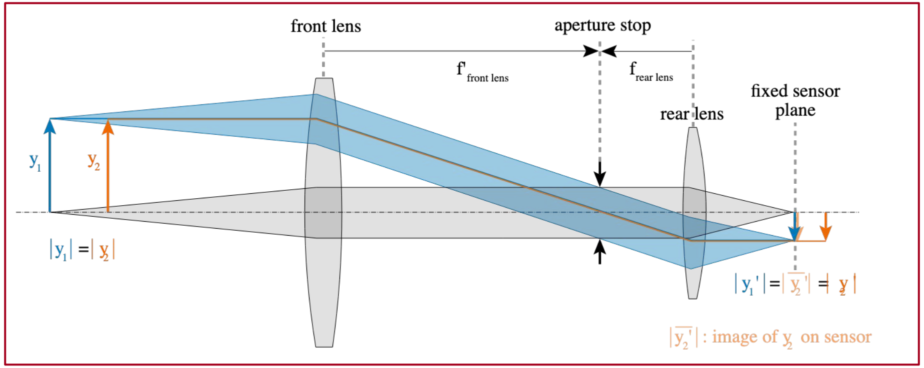


Cross section full detector

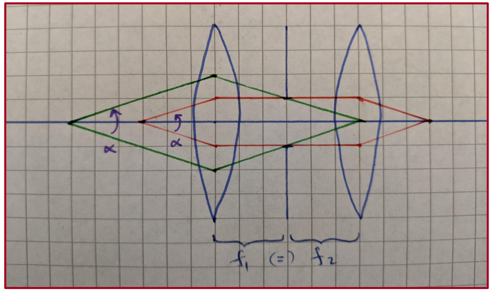
https://indico.fnal.gov/event/19433/session/5/contribution/11/material/slides/0.pdf

Optics for Metrology

- Telecentric lenses allow for imagining true orthographic projections
  - Constant magnification at different depths
  - Equal light collected from different depths (under paraxial approximation)
- Primarily limited by effective F# of the lens
  - Example lens with appropriate working parameters
  - https://www.bhphotovideo.com/c/product/1221754-REG/opto_engineering_tc23048_c_mount_184x_bi_telecentric_lens.html/specs
- 1-1 metrology possible with easier calibration scheme than entocentric systems
  - Known magnification
  - Symmetric blurring

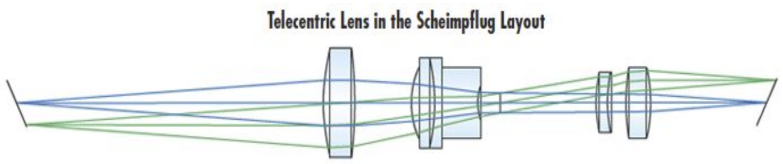


https://www.silloptics.de/en/products/sill-technicon/machine-vision/machine-vision-telecentric-lenses

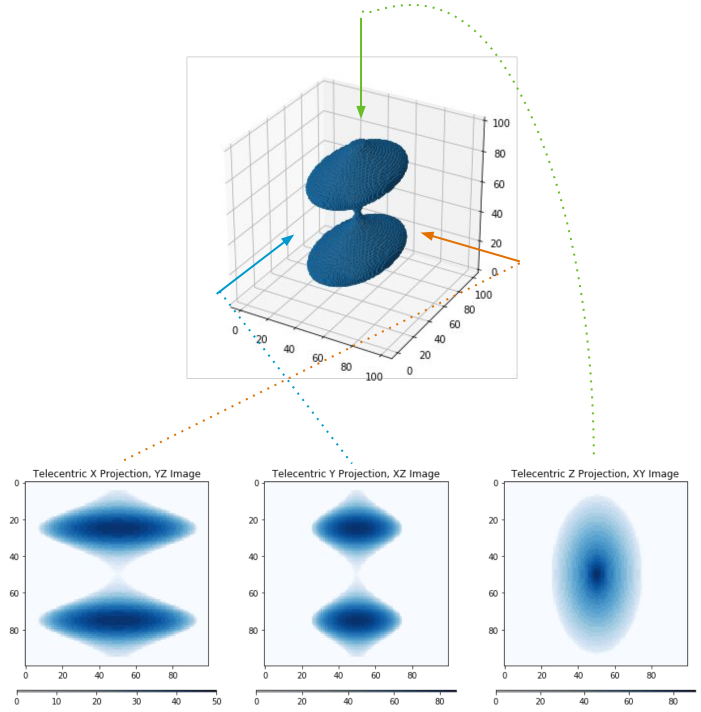


3D Computational Imaging

- Acquire 3 orthogonal images
  - X, Y, Z line integrals
  - Z imaging possible using Mirrors or Scheimpflug tilt (complex DoF)

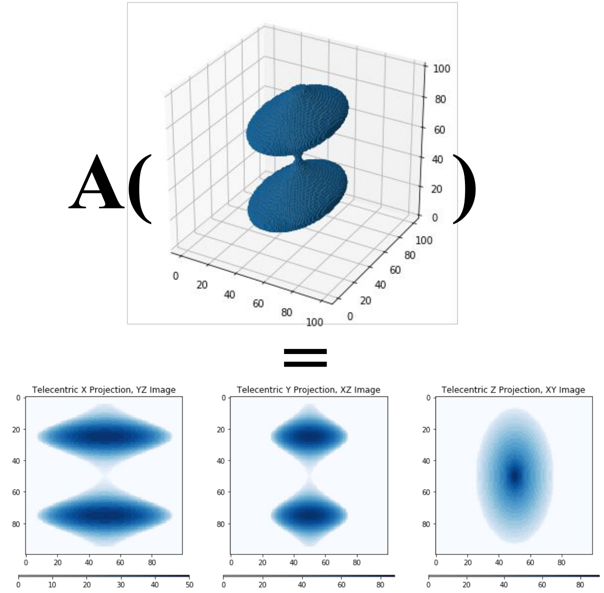


https://www.edmundoptics.com/knowledge-center/application-notes/imaging/advantages-of-telecentricity/



3D Computational Imaging

- Iteratively reconstruct 3D geometry
  - Projection Operator **A** is lossy in $\mathbf{A}(x) = b$
  - $x = \mathbf{A}^{-1}(b)$ relies on guiding priors
  - Minimize $1/2||\mathbf{A}(x) - b||^2 + \mathbf{\Gamma}(x)$
  - Choice of $\mathbf{\Gamma}(x)$ depends on physics of x



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- Iteratively reconstruct 3D geometry
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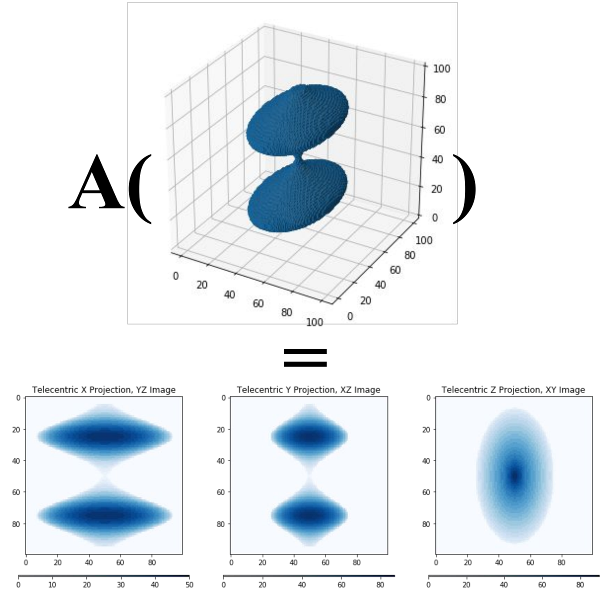
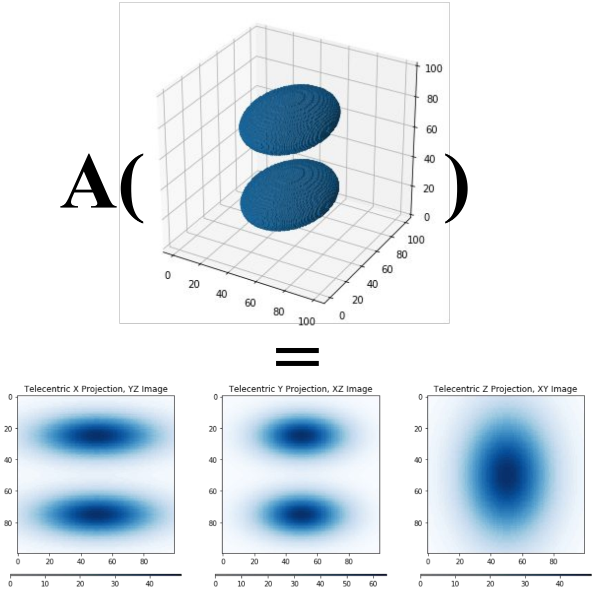
  - Minimize $1/2\|\mathbf{A}(x) - \mathrm{b}\|^2 + \boldsymbol{\Gamma}(x)$
  - Choice of $\boldsymbol{\Gamma}(x)$ depends on physics of x
- Uniform Density Clouds
  - $x(\mathrm{i,j,k}) = 1$ inside bulk of x (cloud), $= 0$ o/w
  - First Derivative of x is sparse
    - Non zero only on the edges
    - $[\mathbf{D}^{(1)}(x)](\mathrm{i,j,k}) = \mathrm{sqrt}\ \{(x(\mathrm{i+1,j,k}) - x(\mathrm{i,j,k}))^2 + (x(\mathrm{i,j+1,k}) - x(\mathrm{i,j,k}))^2 + (x(\mathrm{i,j,k+1}) - x(\mathrm{i,j,k}))^2 \}$
  - $\boldsymbol{\Gamma}(x) = |\mathbf{D}^{(1)}(x)|$
    - L1 Norm encourages sparsity of $\mathbf{D}^{(1)}(x)$



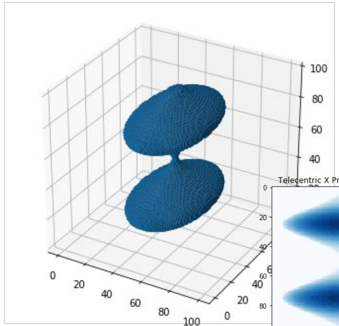
3D Computational Imaging

- Iteratively reconstruct 3D geometry
  - Projection Operator **A** is lossy in $\mathbf{A}(x) = b$
  - $x = \mathbf{A}^{-1}(b)$ relies on guiding priors
  - Minimize $1/2\|\mathbf{A}(x) - b\|^2 + \boldsymbol{\Gamma}(x)$
  - Choice of $\boldsymbol{\Gamma}(x)$ depends on physics of x
- Smoothly Varying Density Clouds
  - First Derivative of x is small/ smooth
  - Second derivative of x can be small and/or sparse
    - $[\mathbf{D}^{(2)}(x)](i,j,k) = \text{sqrt}\ \{(x(i+1,j,k) + x(i-1,j,k) - 2x(i,j,k))^2 + (x(i,j+1,k) + x(i,j-1,k) - 2x(i,j,k))^2 + (x(i,j,k+1) + x(i,j,k-1) - 2x(i,j,k))^2 \}$
  - $\boldsymbol{\Gamma}(x) = |\mathbf{D}^{(2)}(x)|$
    - L1 Norm encourages sparsity. Most general solution
  - $\boldsymbol{\Gamma}(x) = |\mathbf{D}^{(2)}(x)|^2$
    - L2 Norm results in small values of $\mathbf{D}^{(2)}(x)$
    - Limits magnitude of change in $\mathbf{D}^{(1)}(x)$

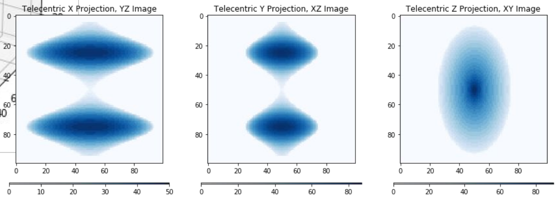


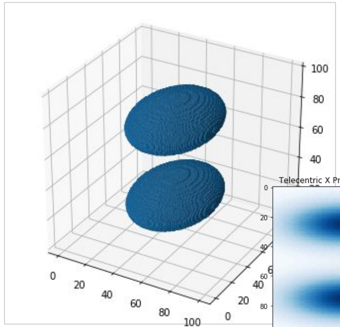
3D Imaging - Proof of Principle Study

- Utilize telecentric/ entocentric projections
- Assume identical pixel illumination, equal magnification at the 3 sensor planes
- Assume atoms clouds are transparent with uniform/ smoothly varying densities
- Input 3 orthogonal images
  - X, Y, Z line integrals
- Iteratively reconstruct 3D geometry
  - Use sparsity or vanishing $\mathbf{D}^{(1)}$ / $\mathbf{D}^{(2)}$ priors
  - ADMM [1] or Conjugate Gradients directly on symmetrized operators

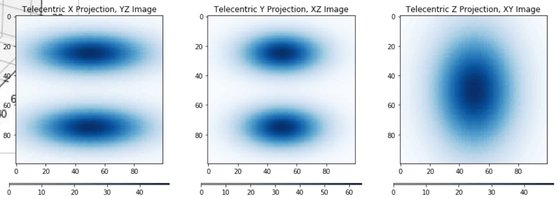


Uniformly dense voxels



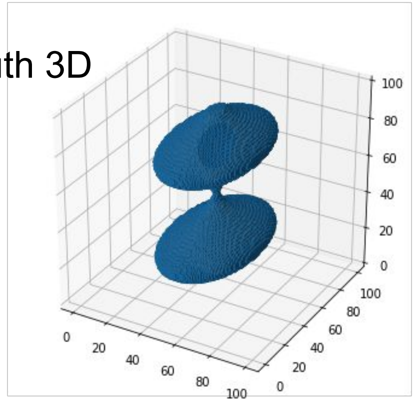


Smoothly dense voxels

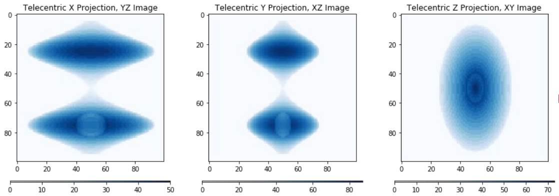


1. Distributed optimization and statistical learning via the alternating direction method of multipliers
S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, 2011
Proximal algorithms, N. Parikh and S. Boyd, 2014

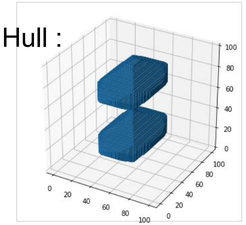
3D Imaging - Uniform Cloud - Results

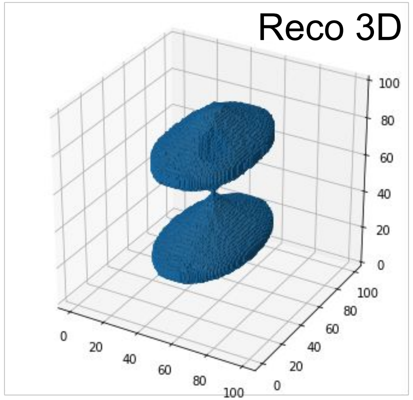


Input

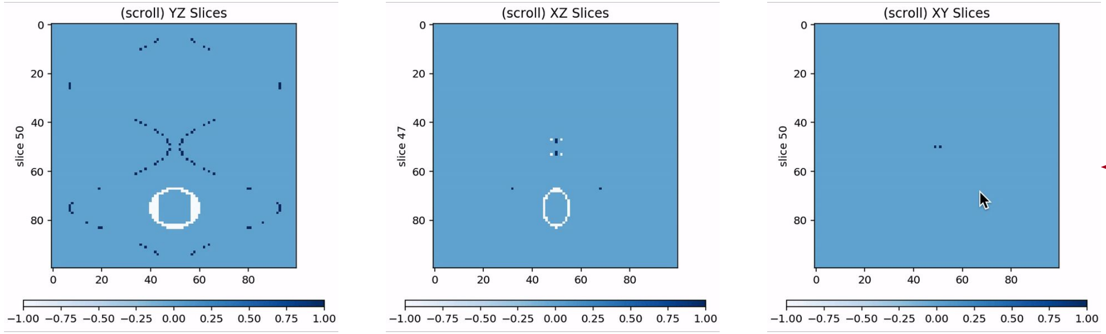


Visual Hull :



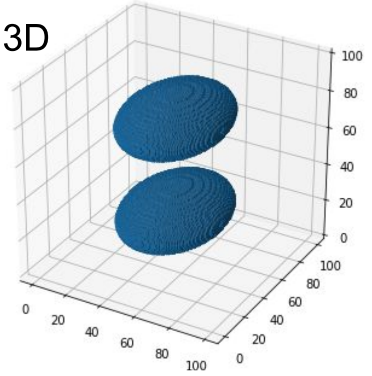


Difference between Truth and Reco Clouds

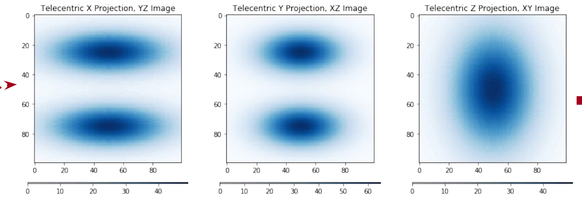


3D Imaging - Smoothly Dense Cloud - Results

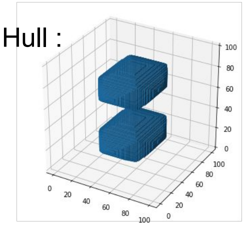
Truth 3D



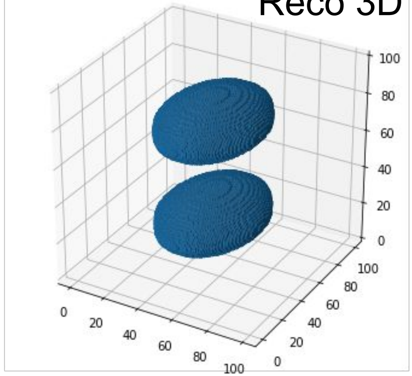
Input



Visual Hull :



Reco 3D



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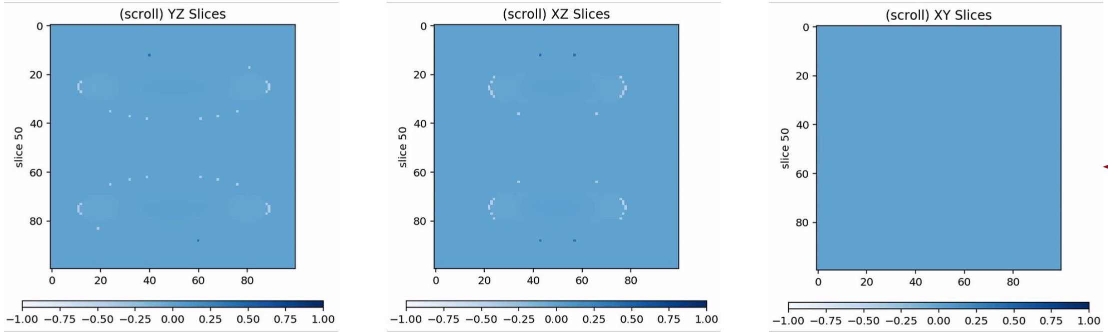
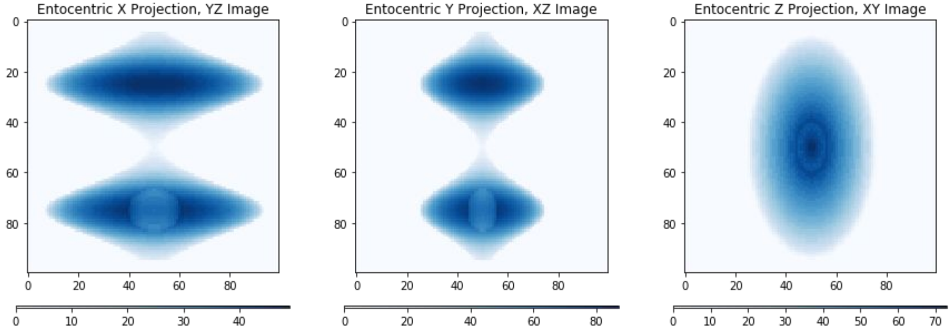
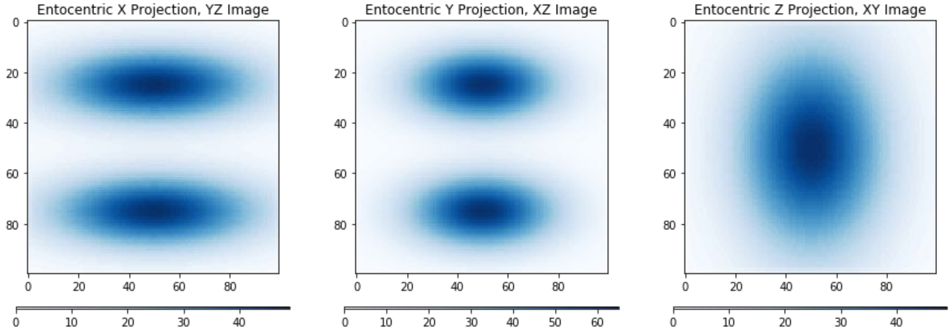


Using Entocentric X, Y, Z Projections

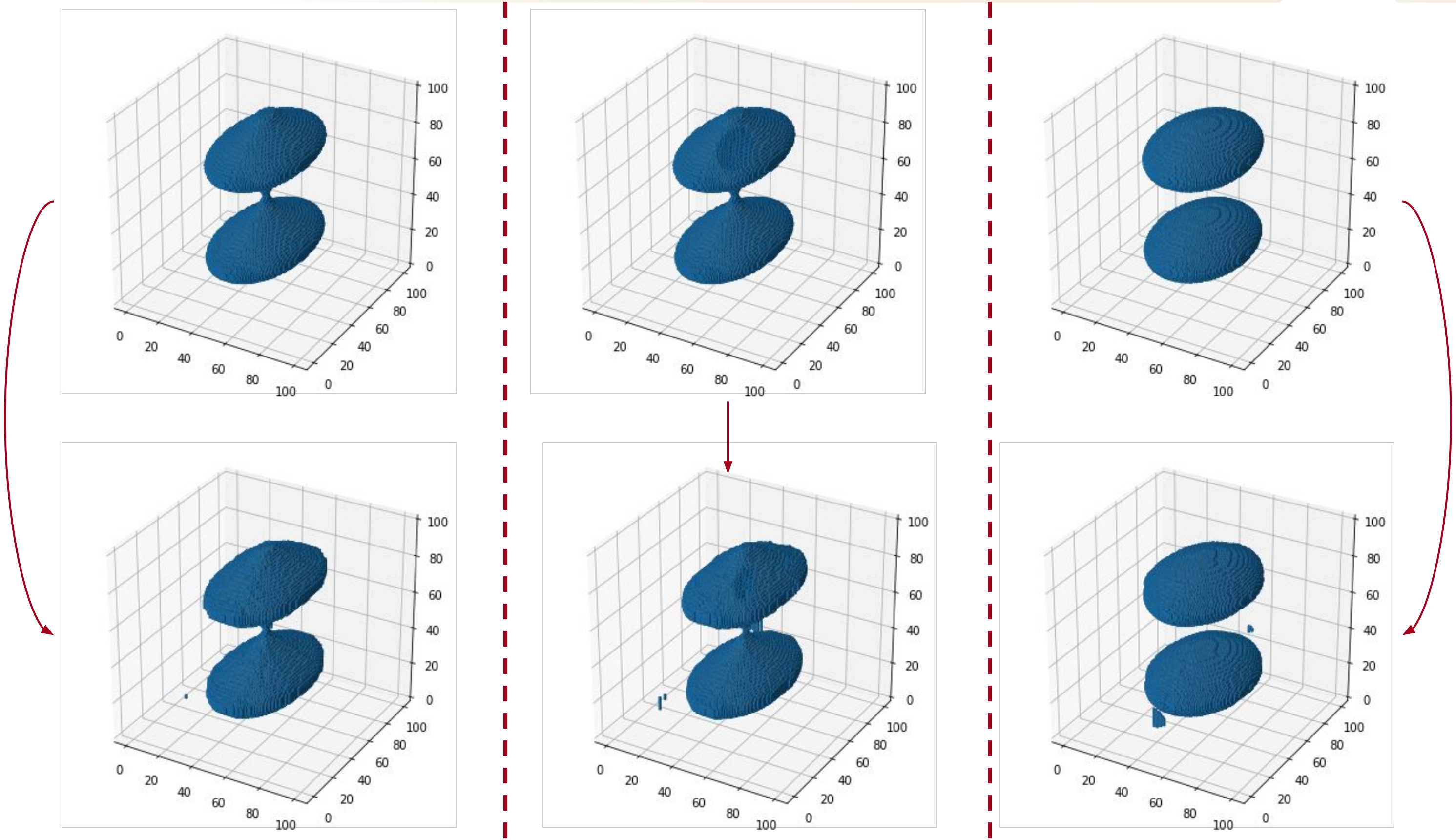
Uniform Cloud with Cavity



Smoothly Varying Density Cloud



Using Entocentric X, Y, Z Projections



Quantitative Results

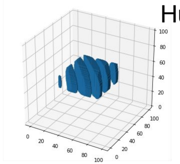
Uniform Cloud with Cavity			Smoothly Varying Density Cloud		
telecentric/ entocentric	**$\|\|D^1(x)\|\|^1$**	**Visual Hull Only**	**$\|\|D^2(x)\|\|^1$**	**$\|\|D^2(x)\|\|^2$**	**Visual Hull Only**
PSNR	25.95 / 20.90	16.96 / 11.76	33.89 / 32.08	29.21 / 8.956	18.69 / 12.49
Recon Err	.0686 / .1314	.1700 / .5639	.0246 / .0361	.0769 / 2.523	.1146 / .4780

PSNR $= 10\log_{10}(1/mean||voxel_{reco} - voxel_{true}||^2)$ Recon Err $= \sum||voxel_{reco} - voxel_{true}||^1/\sum voxel_{true}$

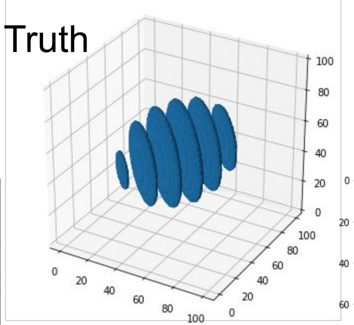
NB Both metrics evaluated after setting $voxel[voxel < 0.4] = 0$

Maximally confused sinusoid in XY plane

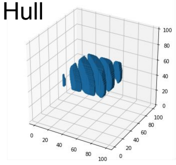
Hull

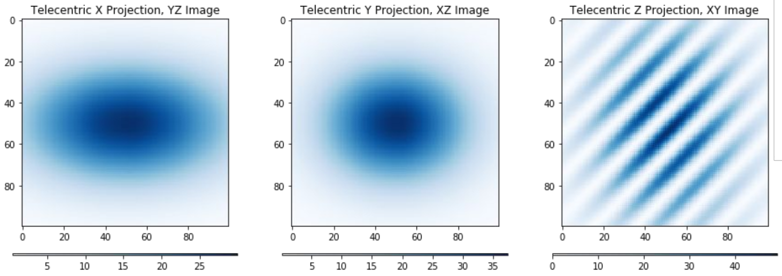


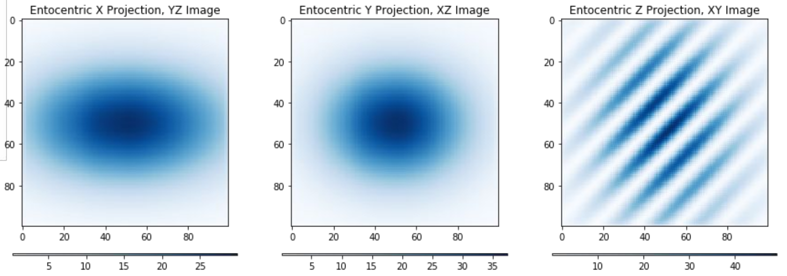
Truth



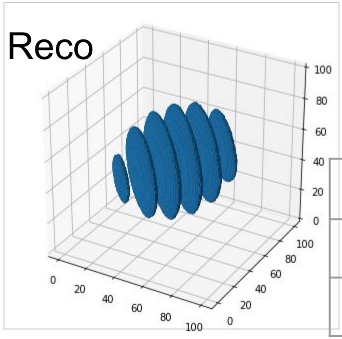
Hull







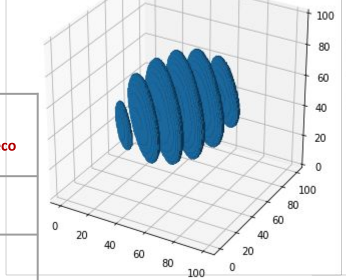
Tele - Reco



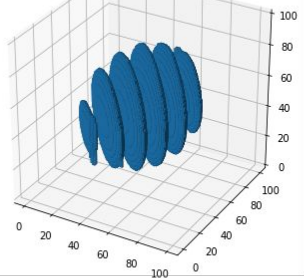
	$\|\|D^2(x)\|\|^1$
PSNR	30.08
Recon Err	0.1058

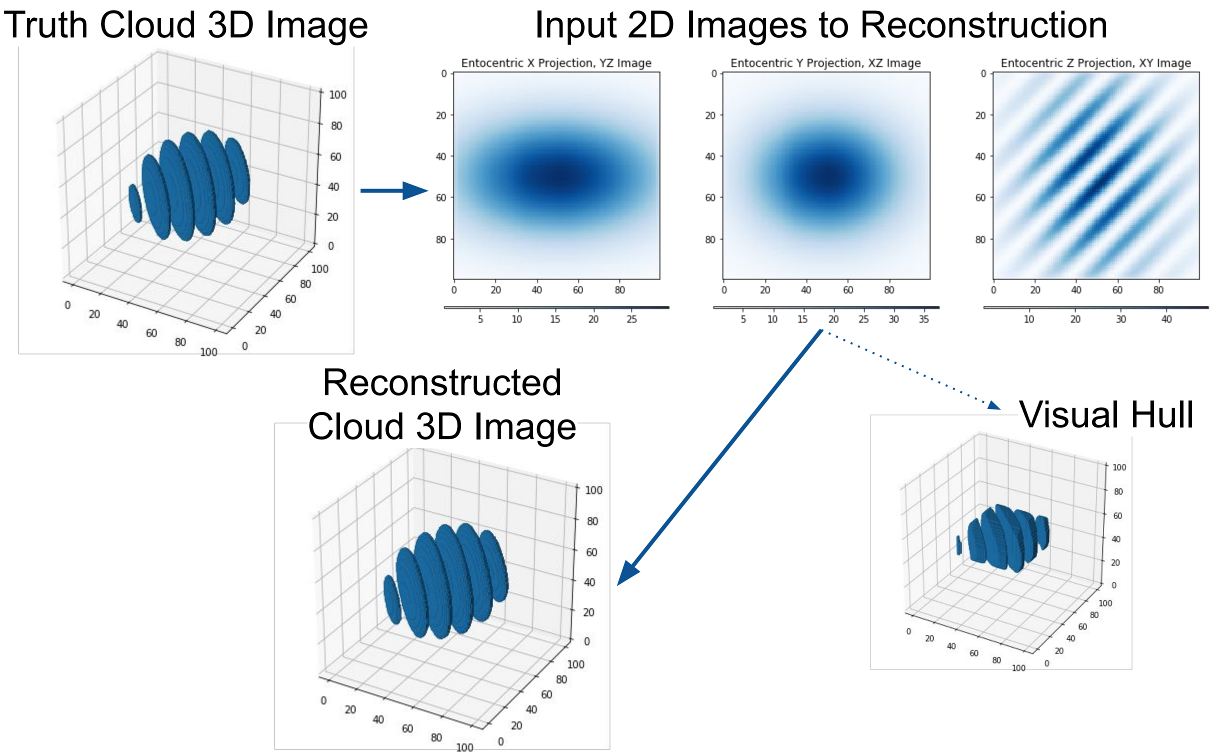
	$\|\|D^2(x)\|\|^1$ Entocentric Reco	$\|\|D^2(x)\|\|^1$ Telecentric Reco
PSNR	26.85	29.71
Recon Err	0.2017	.1112

Tele - Reco



Ento - Reco

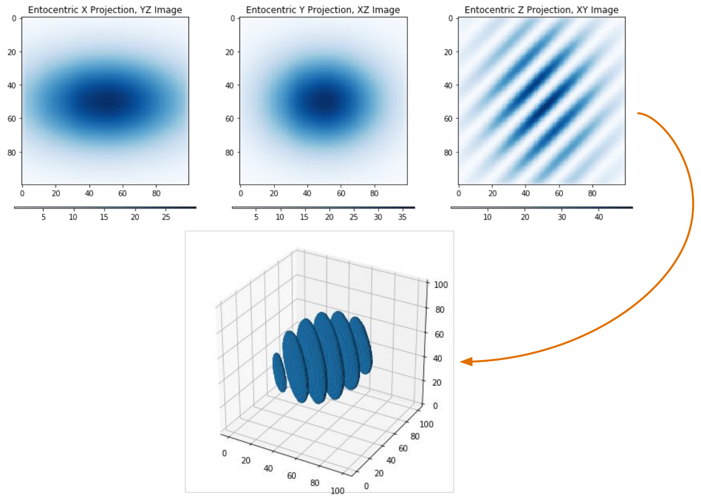



Truth Cloud 3D Image
Input 2D Images to Reconstruction
Entocentric X Projection, YZ Image
Entocentric Y Projection, XZ Image
Entocentric Z Projection, XY Image
Reconstructed Cloud 3D Image
Visual Hull

Summary

- Initial studies towards contributing to the development of a monitoring system for MAGIS-100
- Various optical systems (eg Telecentric) being considered

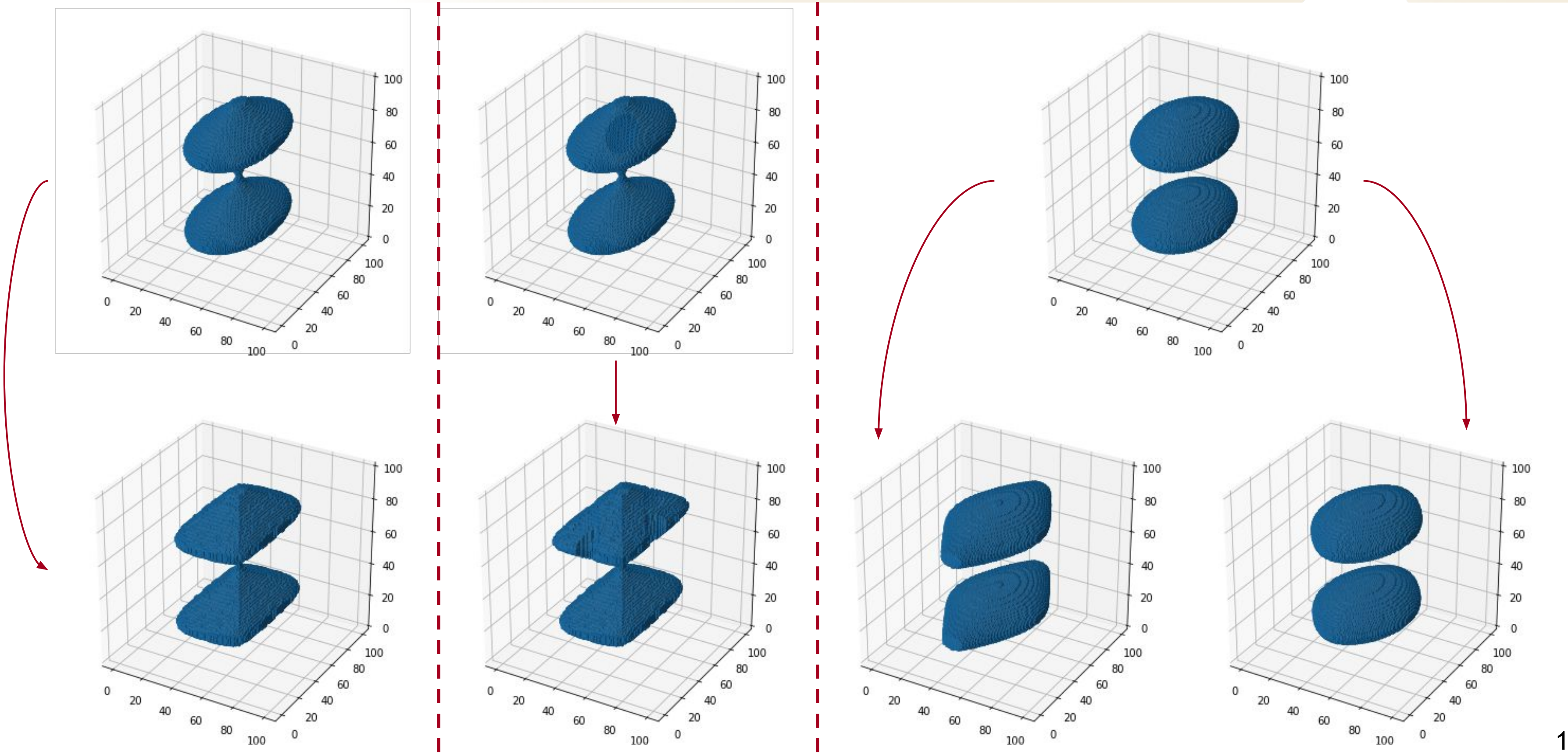
- Studied the potential of 3D atom cloud reconstruction from three 2D images
  - New way of visualizing the 3D details of interfering atom clouds
  - Considered benefits of using telecentric systems
    - Detailed study about light loss needed
    - At current errors entocentric images used with telecentric reconstruction give comparable performance
  - Develop better & more applicable performance metrics



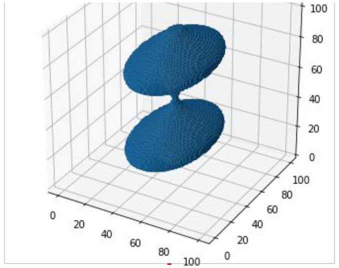
- More work needed to understand advantages of 3D and how it might complement/ enhance 2D imaging methods
- Feedback welcome!

BACKUP

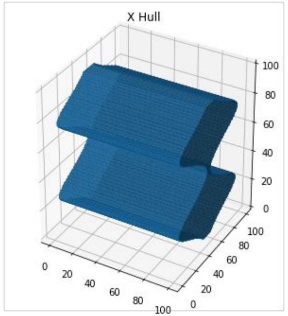
Using only X,Y Projections



Visual Hull



Telecentric



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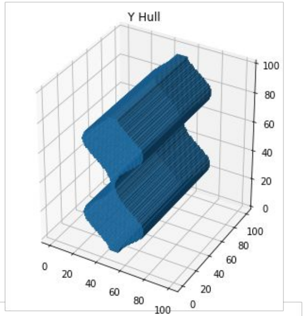

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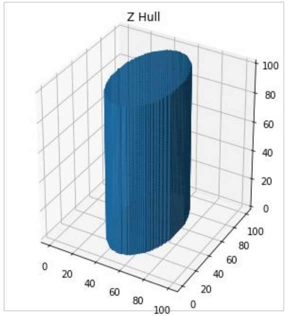
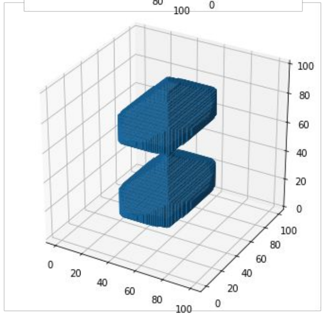
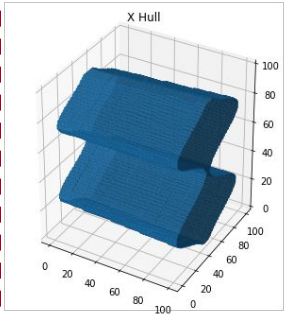




Entocentric



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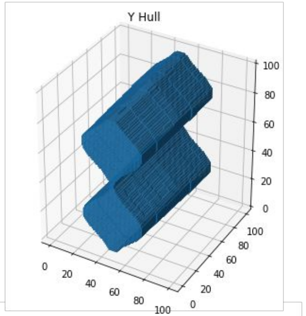

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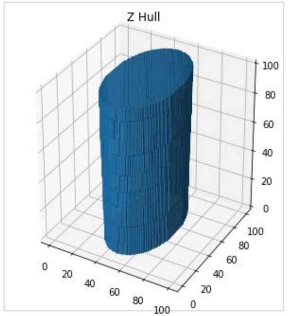
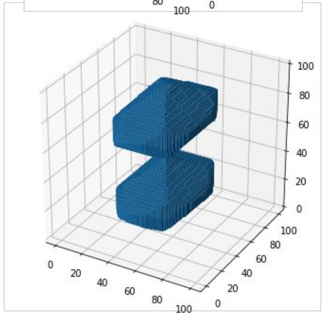
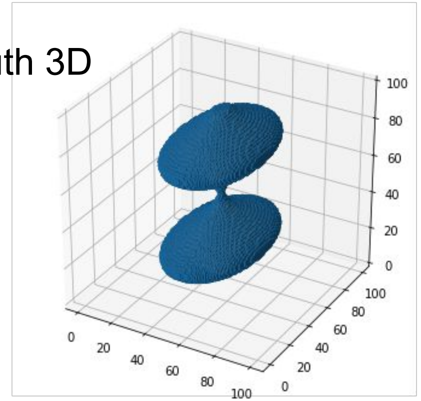


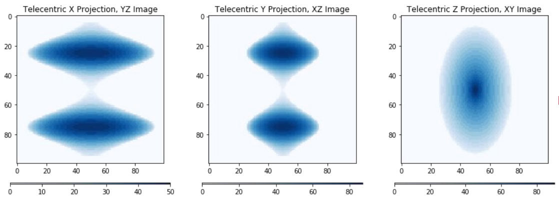


3D Imaging - Simplest Case Qualitative Results

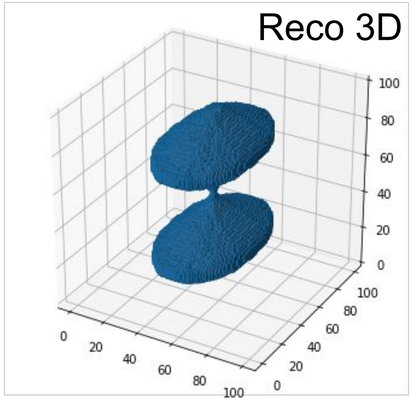
Truth 3D



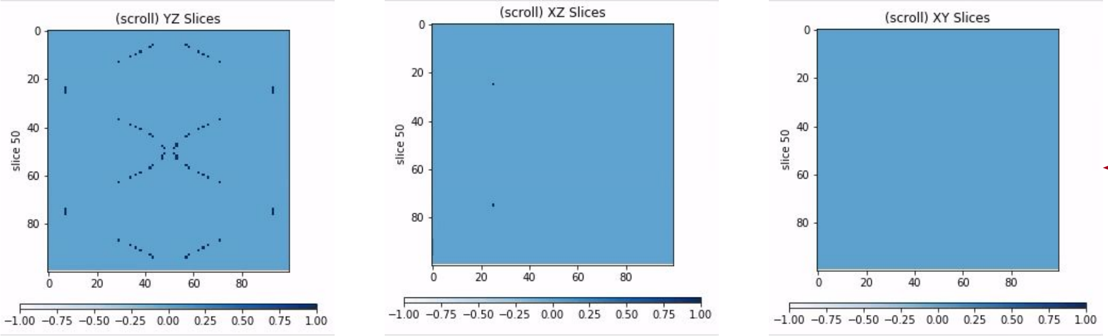
Input



Reco 3D



Difference between Truth and Reco Clouds



Maximally confused sinusoid in X Y Z projections