



**SLAC** NATIONAL  
ACCELERATOR  
LABORATORY

# 3D Reconstruction & Fitting

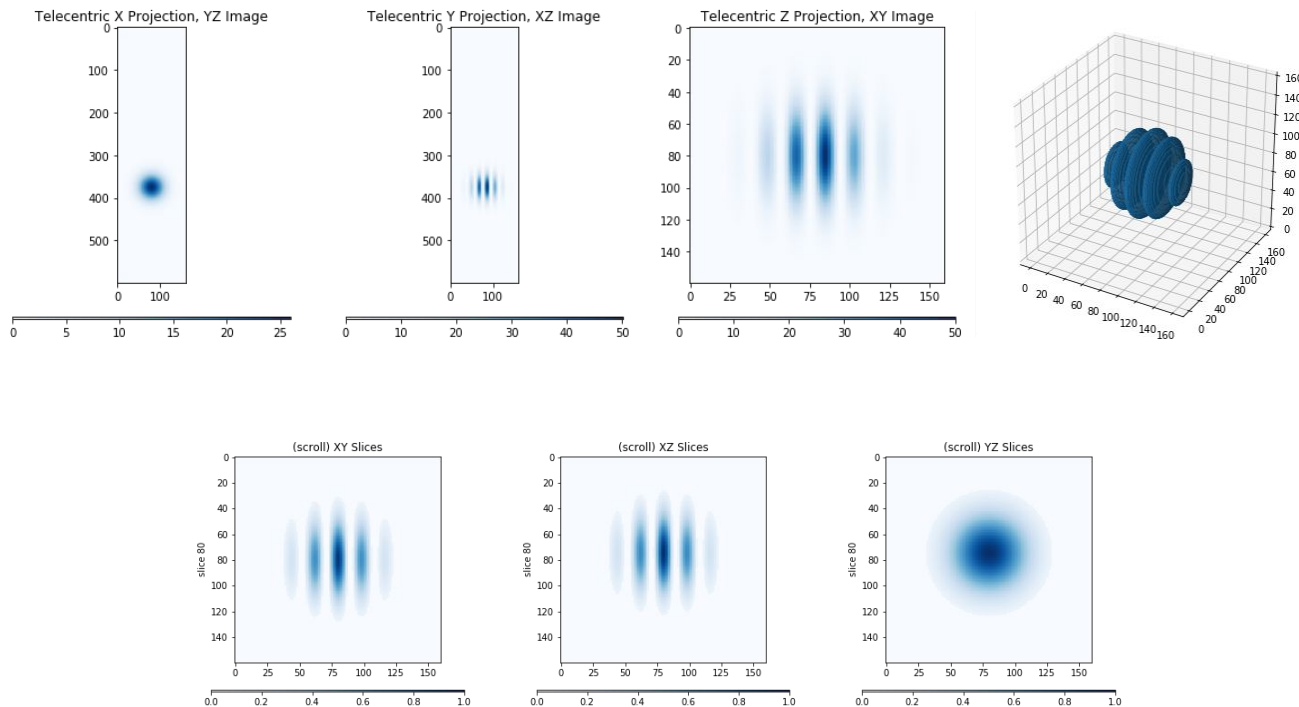
Murtaza Safdari  
Sept 7 2020

$$i \left(\frac{\pi}{\lambda}\right)^{3/4} (mw_0)^{3/2} \left( \frac{1}{\sqrt{2}} + \frac{e^{i(a_{\text{Quad}} k_{\text{Fringe}}^2 x^2 + k_{\text{Fringe}} x)} + i\phi}{\sqrt{2}} \right) e^{-\frac{m((x-x_A)^2 + (y-y_A)^2 + (z-z_A)^2)}{4mw_0^2 + 2i t_{\text{FinalBS}} \hbar}}$$

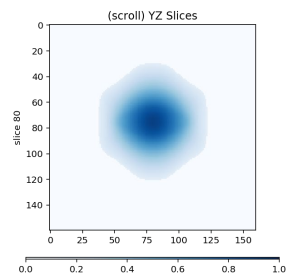
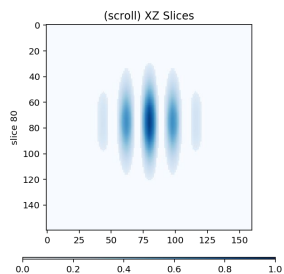
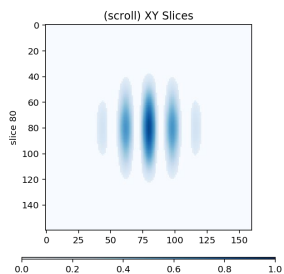
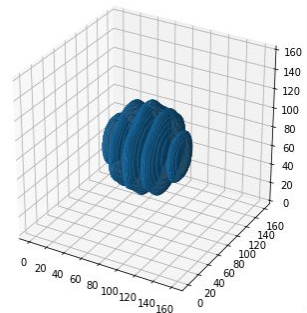
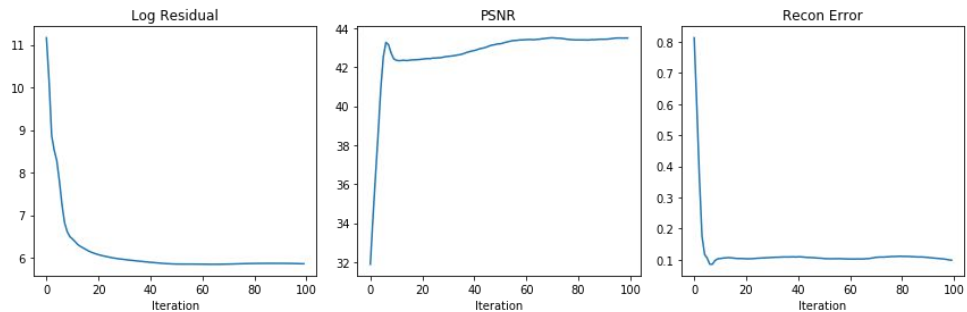

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$$\sqrt{-(2mw_0^2 + i t_{\text{FinalBS}} \hbar)}^3$$

# Inputs



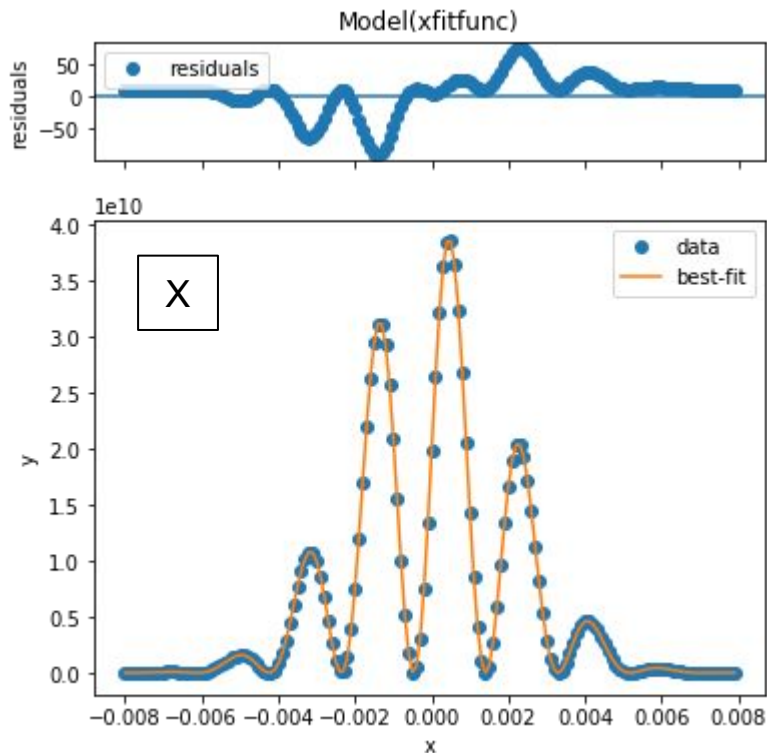
# Current best 3D reconstruction



# 1D Fitting

$$A \cdot N \cdot \left( 1 + \cos \left( \frac{2\pi x}{\lambda \cdot M} + \phi \right) + Q \cdot \left( \frac{2\pi x}{\lambda \cdot M} \right)^2 + \phi \right) \cdot \frac{e^{-\frac{(x-\mu \cdot M)^2}{2\sigma \cdot M^2}}}{\sqrt{2\pi\sigma \cdot M}} + \text{pixelnoise}$$

Using Truth Data



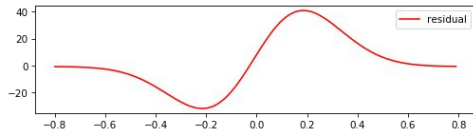
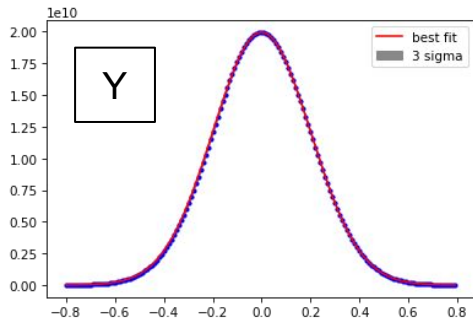
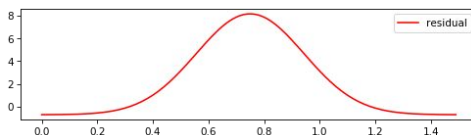
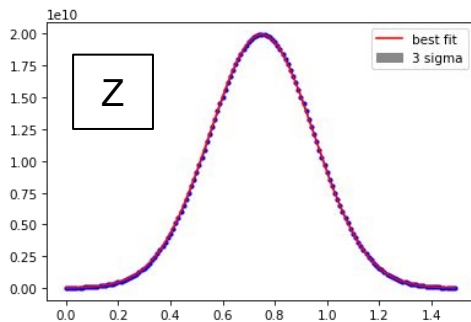
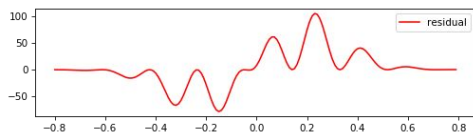
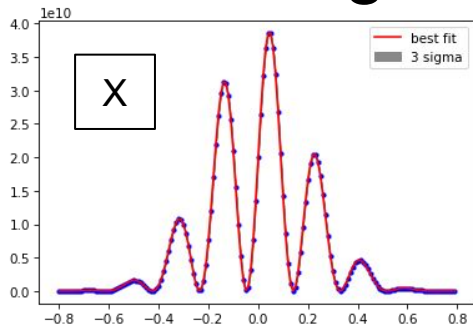
```

[[Model]]
Model(xfitfunc)
[[Fit Statistics]]
# fitting method = leastsq
# function evals = 406
# data points = 160
# variables = 5
chi-square = 151770.399
reduced chi-square = 979.163864
Akaike info crit = 1106.79205
Bayesian info crit = 1122.16792
[[Variables]]
A: 5.6405e+11 +/- 158.660583 (0.00%) (init = 100000)
mu: 7.1959e-12 +/- 3.1796e-13 (4.42%) (init = 0)
sigma: 0.00112838 +/- 3.7419e-13 (0.00%) (init = 0.005)
pixel_noise: 11.6778724 +/- 1.95800145 (16.77%) (init = 0)
phi: -1.57079633 +/- 3.8055e-10 (0.00%) (init = 0)
[[Correlations]] (unreported correlations are < 0.100)
C(A, sigma) = 0.631
C(sigma, pixel_noise) = -0.362
C(A, pixel_noise) = -0.344
C(mu, phi) = -0.201
C(mu, sigma) = -0.126
C(mu, pixel_noise) = -0.103
    
```

# 3D Fitting

$$A \cdot N \cdot \left( 1 + \cos \left( \frac{2\pi x}{\lambda \cdot M} + Q \cdot \left( \frac{2\pi x}{\lambda \cdot M} \right)^2 + \phi \right) \right) \cdot \frac{e^{-\frac{(x-\mu \cdot M)^2}{2\sigma \cdot M^2}}}{\sqrt{2\pi\sigma \cdot M}} + \text{pixelnoise}$$

Using Truth Data



parameter names: ['A', 'mux', 'muy', 'muz', 'sigma', 'pixel\_noise', 'phi']  
 independent variables: ['x', 'y', 'z']

cloud made

(3840000, 1) (3840000, 1) (3840000, 1) (3840000, 1)

[[Model]]

Model(threedfullfitfunc)

[[Fit Statistics]]

# fitting method = leastsq  
 # function evals = 74  
 # data points = 3840000  
 # variables = 7  
 chi-square = 55.3887696  
 reduced chi-square = 1.4424e-05  
 Akaike info crit = -42802953.3  
 Bayesian info crit = -42802861.2

[[Variables]]

A: 2.2448e+08 +/- 4.5595e-04 (0.00%) (init = 5.6e+11)  
 mux: -8.2500e-12 +/- 1.9840e-15 (0.02%) (init = 0)  
 muy: -5.9668e-12 +/- 3.9972e-15 (0.07%) (init = 0)  
 muz: 0.00750000 +/- 5.2360e-15 (0.00%) (init = 0)  
 sigma: 0.00112838 +/- 1.7071e-15 (0.00%) (init = 0.00112837)  
 pixel\_noise: 2.8226e-05 +/- 1.5713e-06 (5.57%) (init = 0)  
 phi: **-1.57079633 +/- 3.2065e-12 (0.00%) (init = -1.570796)**

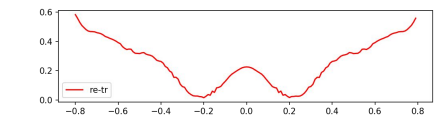
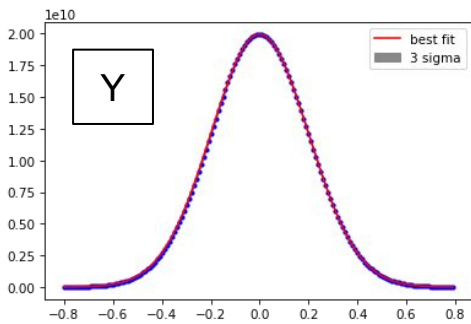
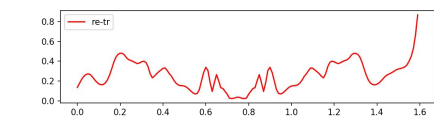
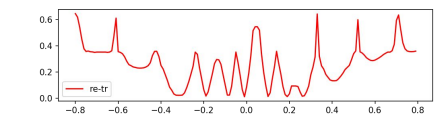
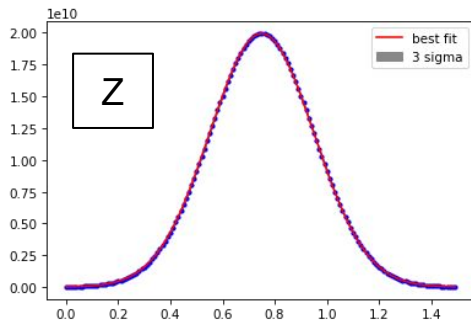
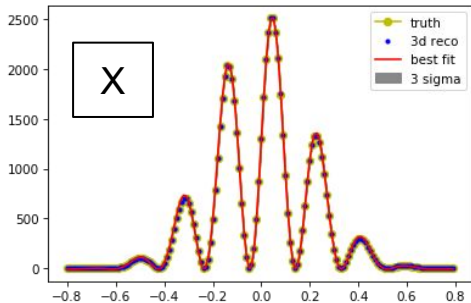
[[Correlations]] (unreported correlations are < 0.100)

C(A, sigma) = -0.375  
 C(A, mux) = -0.175

# 3D Fitting

$$A \cdot N \cdot \left( 1 + \cos \left( \frac{2\pi x}{\lambda \cdot M} + Q \cdot \left( \frac{2\pi x}{\lambda \cdot M} \right)^2 + \phi \right) \right) \cdot \frac{e^{-\frac{(x-\mu \cdot M)^2}{2\sigma \cdot M^2}}}{\sqrt{2\pi\sigma \cdot M}} + \text{pixelnoise}$$

Using 3D Recon.



parameter names: ['A', 'mux', 'muy', 'muz', 'sigma', 'pixel\_noise', 'phi']  
 independent variables: ['x', 'y', 'z']  
 cloud made

(3840000, 1) (3840000, 1) (3840000, 1) (3840000, 1)

[[Model]]

Model(threedfullfitfunc)

[[Fit Statistics]]

# fitting method = leastsq  
 # function evals = 82  
 # data points = 4096000  
 # variables = 7  
 chi-square = 58.3112869  
 reduced chi-square = 1.4236e-05  
 Akaike info crit = -45710222.8  
 Bayesian info crit = -45710130.2

[[Variables]]

A: 14.3273670 +/- 4.4480e-04 (0.00%) (init = 1)  
 mux: -1.5442e-06 +/- 8.2347e-08 (5.33%) (init = 0)  
 muy: -8.9271e-09 +/- 8.2345e-08 (922.42%) (init = 0)  
 muz: 0.00750000 +/- 8.2347e-08 (0.00%) (init = 0)  
 sigma: 0.00115191 +/- 2.8242e-08 (0.00%) (init = 0.00112837)  
 pixel\_noise: -3.2180e-04 +/- 2.0264e-06 (0.63%) (init = 0)  
**phi: -1.57097929 +/- 4.9397e-05 (0.00%) (init = -1.570796)**

[[Correlations]] (unreported correlations are < 0.100)

C(A, sigma) = -0.317  
 C(sigma, pixel\_noise) = -0.313  
 C(A, pixel\_noise) = -0.124

# Summary & Next Steps

- Analogue 3D reconstruction looks good
- Results from fitting to 3D geometries with  $M=1$  looks better than 1D fit on truth data
- Fitting on 3D reconstructed data gives lower performance
  - Effect of inadequate modelling function
- Find data-driven way to learn modeling function from 3D recon clouds
- Add in effects of magnification and entocentricity to gauge degradation in performance
- Add effects of sensor imperfections

# ML approach

- Many ML approaches to 3D reconstruction in literature
  - DOI: [10.1109/ISBI.2018.8363663](https://doi.org/10.1109/ISBI.2018.8363663)
  - DOI: [10.1117/12.2293766](https://doi.org/10.1117/12.2293766)
  - [arXiv:1709.01841](https://arxiv.org/abs/1709.01841)
  - DOI: [10.1088/1361-6420/ab6d57](https://doi.org/10.1088/1361-6420/ab6d57)
  - <https://openreview.net/forum?id=rJed6j0cKX>
- Methods rely on the ability of networks to learn the prior from training data
- Can we generate  $O(e^4-e^6)$  clouds that suitably fill up the physical phase space of clouds we will encounter in MAGIS?
  - Can start at the truth level before adding in detector effects