

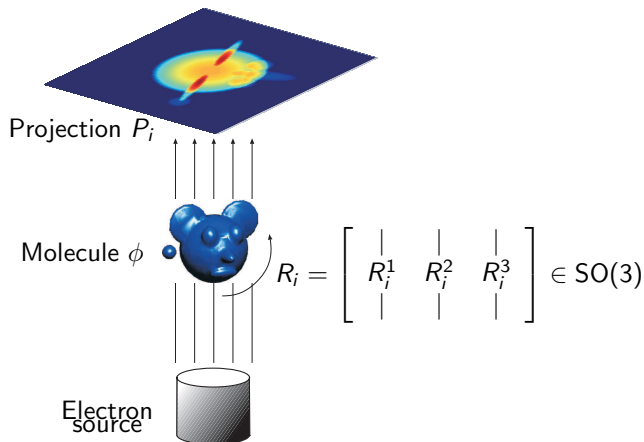
# The Inverse Problem of Cryo-Electron Microscopy

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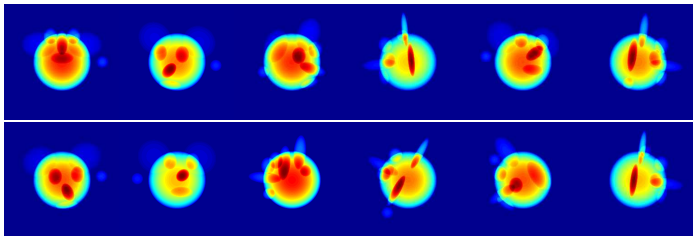
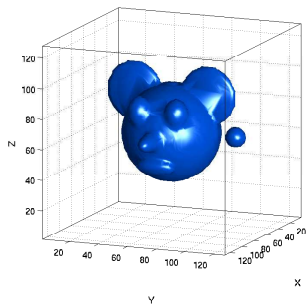
Bridging the Gap Between the Geosciences and Mathematics,  
Statistics, and Computer Science  
October 2, 2012

# Single Particle Cryo-Electron Microscopy: Model



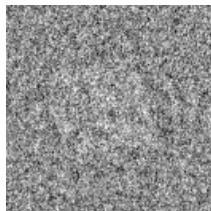
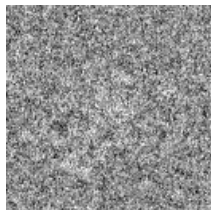
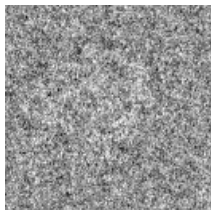
- ▶ Projection images  $P_i(x, y) = \int_{-\infty}^{\infty} \phi(xR_i^1 + yR_i^2 + zR_i^3) dz + \text{"noise"}$ .
- ▶  $\phi : \mathbb{R}^3 \mapsto \mathbb{R}$  is the electric potential of the molecule.
- ▶ Cryo-EM problem: Find  $\phi$  and  $R_1, \dots, R_n$  given  $P_1, \dots, P_n$ .

# Toy Example

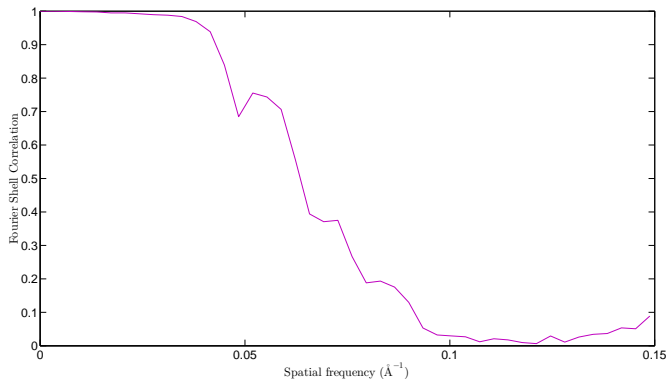


# E. coli 50S ribosomal subunit: sample images

Fred Sigworth, Yale Medical School



# Movie by Lanhui Wang and Zhizhen (Jane) Zhao



# Algorithmic Pipeline

- ▶ **Particle Picking:** manual, automatic or experimental image segmentation.
- ▶ **Class Averaging:** classify images with similar viewing directions, register and average to improve their signal-to-noise ratio (SNR).  
*S, Zhao, Shkolnisky, Hadani, SIIMS, 2011.*
- ▶ **Orientation Estimation:**  
*S, Shkolnisky, SIIMS, 2011.*
- ▶ **Three-dimensional Reconstruction:** a 3D volume is generated by a tomographic inversion algorithm.
- ▶ **Iterative Refinement**

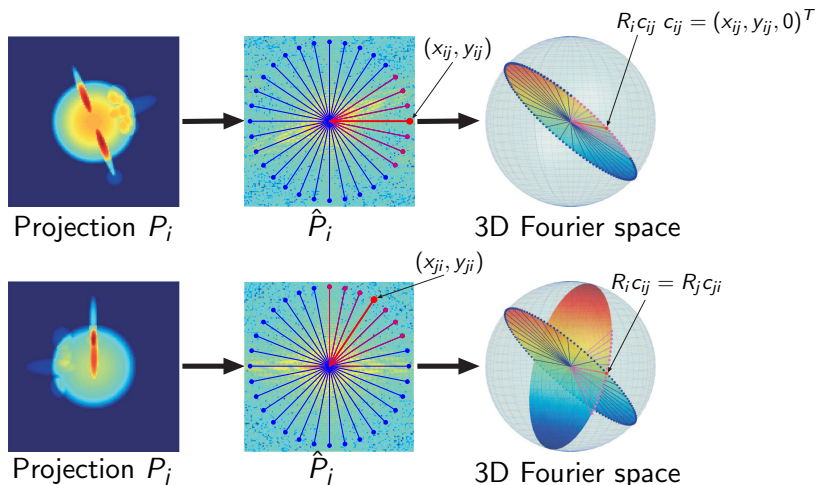
## Assumptions for Today's talk:

- ▶ Trivial point-group symmetry
- ▶ Homogeneity

# What mathematics do we use to solve the inverse problem?

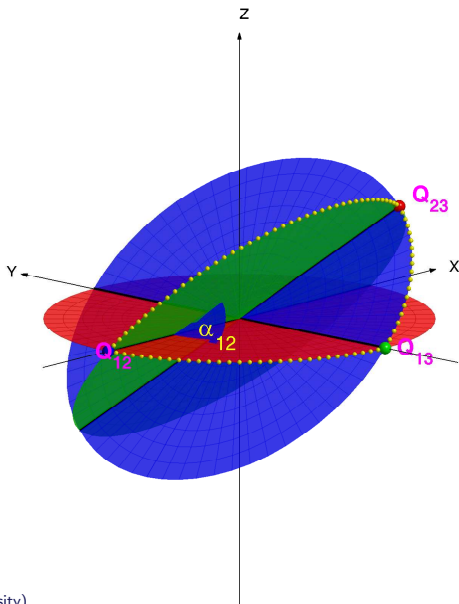
- ▶ Tomography
- ▶ Convex optimization and semidefinite programming
- ▶ Random matrix theory (in several places)
- ▶ Representation theory of  $SO(3)$  (spherical harmonics)
- ▶ Spectral graph theory, (vector) diffusion maps
- ▶ Fast randomized algorithms
- ▶ ...

# Orientation Estimation: Fourier projection-slice theorem





# Angular Reconstitution (Van Heel 1987, Vainshtein and Goncharov 1986)



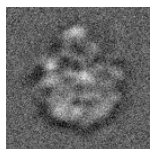
## Experiments with simulated noisy projections

- ▶ Each projection is 129x129 pixels.

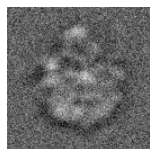
$$\text{SNR} = \frac{\text{Var}(\text{Signal})}{\text{Var}(\text{Noise})},$$



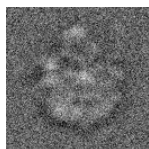
(a) Clean



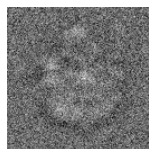
(b)  $\text{SNR}=2^0$



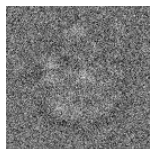
(c)  $\text{SNR}=2^{-1}$



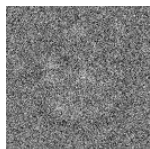
(d)  $\text{SNR}=2^{-2}$



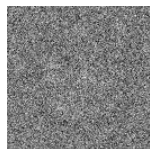
(e)  $\text{SNR}=2^{-3}$



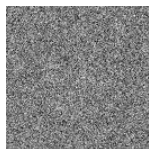
(f)  $\text{SNR}=2^{-4}$



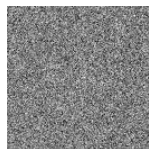
(g)  $\text{SNR}=2^{-5}$



(h)  $\text{SNR}=2^{-6}$



(i)  $\text{SNR}=2^{-7}$



(j)  $\text{SNR}=2^{-8}$

## Fraction of correctly identified common lines and the SNR

- ▶ Define common line as being correctly identified if both radial lines deviate by no more than  $10^\circ$  from true directions.
- ▶ Fraction  $p$  of correctly identified common lines increases by PCA

$\log_2(\text{SNR})$	$p$
20	0.997
0	0.980
-1	0.956
-2	0.890
-3	0.764
-4	0.575
-5	0.345
-6	0.157
-7	0.064
-8	0.028
-9	0.019

## Least Squares Approach

- ▶ Consider the unit directional vectors as three-dimensional vectors:

$$c_{ij} = (x_{ij}, y_{ij}, 0)^T,$$

$$c_{ji} = (x_{ji}, y_{ji}, 0)^T.$$

- ▶ Being the common-line of intersection, the mapping of  $c_{ij}$  by  $R_i$  must coincide with the mapping of  $c_{ji}$  by  $R_j$ : ( $R_i, R_j \in SO(3)$ )

$$R_i c_{ij} = R_j c_{ji}, \text{ for } 1 \leq i < j \leq n.$$

- ▶ Least squares or Energy minimization:

$$\min_{R_1, R_2, \dots, R_n \in SO(3)} \sum_{i \neq j} \|R_i c_{ij} - R_j c_{ji}\|^2$$

- ▶ Non-convex... Exponentially large search space...

# Spectral Relaxation for Uniformly Distributed Rotations

$$\tilde{R}_i = \begin{bmatrix} | & | \\ R_i^1 & R_i^2 \\ | & | \end{bmatrix} = \begin{bmatrix} x_i^1 & x_i^2 \\ y_i^1 & y_i^2 \\ z_i^1 & z_i^2 \end{bmatrix}, \quad i = 1, \dots, n.$$

- ▶ Define 3 vectors of length  $2n$

$$x = [x_1^1 \quad x_1^2 \quad x_2^1 \quad x_2^2 \quad \dots \quad x_n^1 \quad x_n^2]^T$$

$$y = [y_1^1 \quad y_1^2 \quad y_2^1 \quad y_2^2 \quad \dots \quad y_n^1 \quad y_n^2]^T$$

$$z = [z_1^1 \quad z_1^2 \quad z_2^1 \quad z_2^2 \quad \dots \quad z_n^1 \quad z_n^2]^T$$

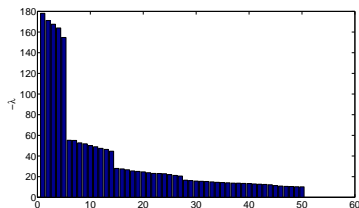
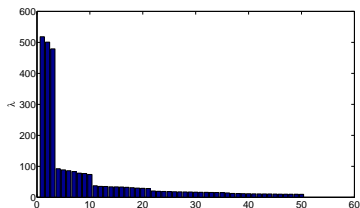
- ▶ Rewrite the objective function as

$$\max_{R_1, \dots, R_n \in SO(3)} \sum_{i \neq j} \langle R_i c_{ij}, R_j c_{ji} \rangle = \max_{R_1, \dots, R_n \in SO(3)} x^T C x + y^T C y + z^T C z$$

- ▶ By **symmetry**, if rotations are uniformly distributed over  $SO(3)$ , then the top eigenvalue of  $C$  has multiplicity 3 and corresponding eigenvectors are  $x, y, z$  from which we recover  $R_1, R_2, \dots, R_n!$

## Spectrum of $C$

- ▶ Numerical simulation with  $n = 1000$  rotations sampled from the Haar measure; no noise.
- ▶ Bar plot of positive (left) and negative (right) eigenvalues of  $C$ :



- ▶ Eigenvalues:  $\lambda_l \approx n \frac{(-1)^{l+1}}{l(l+1)}$ ,  $l = 1, 2, 3, \dots$  ( $\frac{1}{2}, -\frac{1}{6}, \frac{1}{12}, \dots$ )
- ▶ Multiplicities:  $2l + 1$ .
- ▶ Two basic questions:
  1. Why this spectrum? Answer: Representation Theory of  $SO(3)$  (Hadani, S, 2011)
  2. Is it stable to noise? Answer: Yes, due to random matrix theory.