

3D reconstruction

Reconstruction is the process to obtain from 2D images of particles the 3D map of electrostatic potential (volume of the object)



The reconstruction is carried on in 2 steps:

- 1. Determination of the Euler angles of each particle image
- 2. Reconstruction of the volume from the images with assigned angles





Some basic ideas...

Euler angles:

Rotation angles of each particle compared to the incident electron beam, determining the projection of particles in a different orientation





Projection:

The image of the particle obtained from the micrographs is NOT just the shape of the molecule, but the **projection of the electrostatic potential** of the protein: features are present in the interior of particles.





Step 1: Euler angles determination

For reconstruction, projections of the particles in different orientations are required.

To each particle orientation (Euler angles) must be assigned.

Reconstruction from many images of the same particle in different orientations:

ELECTRON TOMOGRAPHY

Relative orientation of images is known from the experiment: tilt angle





Random Conical Tilt Method

For grids with preferential orientation (e.g. negative staining) Collection of 'tilt pairs' – 45° and 0° tilt







- 1. Data collection: collect a 45°-tilted image
- Data collection: on the same grid position, collect untilted image
 0°-tilt images will not be used for final 3D reconstruction, but only for identification of Euler angles.
- Interactive windowing of particles in the two micrographs. Centering and masking.

At 0° tilt, projections of the same object are identical except for in-plane rotation (Euler angle φ). At 45°, particles are different.

4. Alignment and classification of particles from 0°-tilt to identify ϕ_i .

Other Euler angles identified from tilt geometry. Determination of correct tilt geometry is crucial!

5. Scaling of tilted data.











0°





Projection Theorem (or Radon's Theorem)

In reciprocal space, every 2D projection of a 3D object corresponds to a 2D central section of the 3D Fourier transform of the object.

The central section obtained from the Fourier transform of a projection is orthogonal to the direction of the projection.

Considering this theorem, the reconstruction of the object from 2D projections is possible, but...

- (1) How many images are required?What is the necessary coverage of the reciprocal space?
- (2) Would reconstruction be unique?

3 Common-Lines Method If images of particles are collected in random orientations (e.g. cryo-EM):





Considering the projection theorem, each FT of a projection includes the center of the Fourier space.

Two FTs of different projections share a **common line**.

Addition of a third projection allows to identify common lines between this and the previous projections...

and to determine relative Euler angles.

Step 2: Reconstruction

- Can we reconstruct the initial volume with an uneven angular distribution?
- How does noise affect the reconstruction?
- How to incorporate constraints?

Methods:



1) Weighted back projection: reconstruction of the volume in real space, using a function that inverts the projection.

However, the sampling in Fourier space is not homogeneous: high frequencies are less sampled than low frequencies, causing reduction of resolution.

Weights applied to images before reconstruction to restore high resolution information $\left(\frac{1}{1-t} for H(s) > T\right)$

$$W(s) = \begin{cases} \frac{\overline{H(s)}}{H(s)} & \text{for } H(s) \ge T\\ \frac{1}{T} & \text{for } H(s) < T \end{cases}$$



2) **Fourier reconstruction methods**: reconstruction in reciprocal space, from the Fourier transforms of each image aligned by Euler angles

Interpolation problem due to non-homogeneous sampling of the reciprocal space. This method is computationally intense

Simultaneous Iterative Algebraic Reconstruction Method (SIRT): 3) reconstruction in reciprocal space, from the Fourier transforms of each image aligned by Euler angles

For each pixel $p_j^{(i)}$ of the i-th projection $p_i^{(i)} = \sum w_{ki}^{(i)} p_k$

$$p_j^{(l)} = \sum_k w_{kj}^{(l)} p_k$$

 p_k = each voxel of the object $w_{ki}^{(i)}$ = weight reflecting orientation of the i-th projection and contribution of the object voxels to the projection

Iterative inversion of the matrix to obtain p_k , computing at each step distances between the experimental projections and the computed projections

CTF correction

CTF correction can be applied:

- On single raw images or micrographs, but this approach is limited due to SNR of single images
- Application of CTF correction after reconstruction, by dividing particles into defocus groups based on original micrographs. (But defocus groups should have a small step to avoid errors in CTF correction that would decrease resolution.)
- Simultaneous CTF correction and reconstruction, using iterative methods... see next slides (Relion, Freealign...)

* For Random Conic Tilt approach, additional problem due to different defocus of particles in 45°-tilted micrographs (according to position of the particle in the micrograph...)

Heterogeneity

Is it possible to separate images from different conformations of the protein/complex in the sample?

all particles **3D** Classification 2D classification & Refinement ribosomal particles **3D** refinement (RELION) reference ribosome **3D** classification **Classification based** 13% 5% on a 3D model: previous structure obtained from X-ray crystallography, Negative Staining EM, ab initio cryo-EM reconstruction 80S + eEF2 80S + tRNAs 80S + tRNAs 80S 60S + elF6 + partial A site density **3D** classification Iterative refinement: use model of the previous 36% cycle to estimate Euler angles (and CTF and/or Class **3D** refinement assignment), movie processing reconstruct model using back projection, until changes are negligible

empty A site

occupied A site

eRF1^{AAQ}-ABCE1 termination complex

Statistical approach





Iterative algorithm





FT(model) *V*⁽⁰⁾

 $\Gamma_{i\phi}^{(1)} \propto \prod_{j} \frac{1}{2\pi\sigma_{ij}^{2}} \exp\left[\frac{\left|X_{ij} - CTF_{ij}\sum_{l} \mathbf{P}_{jl}^{\phi} V_{l}^{0}\right|^{2}}{-2\sigma_{ij}^{2}}\right]$ $V_{l}^{(1)} \propto \sum_{l} \left\{\int_{\phi} \left[\Gamma_{i\phi} \cdot \left(\sum_{j} \mathbf{P}_{jl}^{\phi T} X_{ij}\right)\right] d\phi\right\}$ $\sigma_{ij}^{2(1)} = \frac{1}{2} \int_{\phi} \Gamma_{i\phi}^{(1)} \cdot \left|X_{ij} - CTF_{ij}\left(\sum_{l} \mathbf{P}_{jl}^{\phi} V_{kl}\right)\right|^{2} d\phi$ $\tau_{l}^{2(1)} = \frac{1}{2} \left|V_{l}^{(1)}\right|^{2}$

Calculate:

- Probability distribution of orientations, $\Gamma_{i\phi}{}^{(1)}$, by comparing FT of images with slices of the Fourier space, weighted by the noise of each image.

- The new model, $V^{(1)}$, by back-projecting each image, with orientations weighted by their probability (and with an additional Weiner filter).

- The variance of the noise, $\sigma_{ij}{}^{2(1)}$, and the variance of the signal, $\tau_l{}^{2(1)}$ (used in the Weiner filter).

Iterative algorithm



 $\stackrel{\mathsf{FT}(\mathsf{imgs})}{\longleftrightarrow}$

FT(model)

$\Gamma_{i\phi}^{(n+1)} \propto \prod_{j} \frac{1}{2\pi\sigma_{ij}^{2(n)}} \exp\left(\frac{\left|X_{ij} - CTF_{ij}\sum_{l} \mathbf{P}_{jl}^{\phi} V_{l}^{(n)}\right|^{2}}{-2\sigma_{ij}^{2(n)}}\right)$ $V_{l}^{(n+1)} \propto \sum_{l} \left\{\int_{\phi} \left[\Gamma_{i\phi}^{(n)} \cdot \left(\sum_{j} \mathbf{P}_{jl}^{\phi T} X_{ij}\right)\right] d\phi\right\}$ $\sigma_{ij}^{2(n+1)} = \frac{1}{2} \int_{\phi} \Gamma_{i\phi}^{(n)} \cdot \left|X_{ij} - CTF_{ij}\left(\sum_{l} \mathbf{P}_{jl}^{\phi} V_{kl}^{(n)}\right)\right|^{2} d\phi$ $\tau_{l}^{2(n+1)} = \frac{1}{2} \left|V_{l}^{(n)}\right|^{2}$

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Iterative algorithm





FT(model)

 $\Gamma_{ik\phi}^{(n+1)} \propto \prod_{j} \frac{1}{2\pi\sigma_{ij}^{2(n)}} \exp\left(\frac{\left|X_{ij} - CTF_{ij}\sum_{j}\mathbf{P}_{jl}^{\phi}V_{kl}^{(n)}\right|^{2}}{-2\sigma_{ij}^{2(n)}}\right)$ $V_{kl}^{(n+1)} \propto \sum_{l} \left\{\int_{\phi} \left[\Gamma_{ik\phi}^{(n)} \cdot \left(\sum_{j}\mathbf{P}_{jl}^{\phi T}X_{ij}\right)\right] d\phi\right\}$ $\sigma_{ij}^{2(n+1)} = \frac{1}{2}\sum_{k} \left\{\int_{\phi} \Gamma_{i\phi}^{(n)} \cdot \left|X_{ij} - CTF_{ij}\left(\sum_{l}\mathbf{P}_{jl}^{\phi}V_{kl}^{(n)}\right)\right|^{2} d\phi\right\}$ $\tau_{kl}^{2(n+1)} = \frac{1}{2}\left|V_{kl}^{(n)}\right|^{2}$

Calculate:

- Probability distribution of orientations, $\Gamma_{i\phi}^{(n+1)}$, by comparing FT of images with slices of the Fourier space, weighted by the noise of each image.

- The new model, $V^{(n+1)}$, by back-projecting each image, with orientations weighted by their probability (and with an additional Weiner filter).

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3D classification: K different classes, calculates one volume for each class $V_k^{(n+1)}$

Structure Validation

Sources of error in Single Particle EM structure determination:

- Particle picking from template can create **model bias** (Einstein from noise)

- **Heterogeneity** of sample can create spurious features

- For NS: artifacts of stain

- Lack of completeness (preferred orientation in NS, but also in cryo)

- Model bias in 3D reconstruction
- **Overfitting** (alignment of noise)

Check samples using NS-EM first, to assess homogeneity of particles

VALIDATION!!!

Check reconstruction results:

- Reconstruction with different software
- Compare with previous results (MX, NMR, MD, NS-EM, etc.)
- Ab initio reconstruction avoids model bias
 - Validate with tilt pairs

Carefully assess RESOLUTION!!



HIV-1 envelope glycoprotein





Evaluation of the quality of a structure

Determining quality of the structure is important to understand reliability of structural details

Unlike MX, no R index is available in electron microscopy to directly compare model and data.

However...

 Completeness of the dataset can be evaluated by analysis of orientation frequency of particles







2) Resolution: Unlike MX, resolution has to be determined after data processing and structure solution

Fourier Shell Correlation (FSC)

In the Fourier space, cross correlation coefficients are calculated comparing shells of the Fourier space of the model and of the experimental data

3) Model bias?

Fourier Shell Correlation Gold Standard: dataset is divided in 2, each half refined independently using a low-pass filtered model, FSC calculated between 2 halves

From FSC Gold Standard, resolution can be evaluated, but threshold is still a matter of debate...



Ryanodine Receptor

Before DDD camera



Transient Receptor Potential chennel

Cheng group (UCSF) 2013 - 3.2Å resolution



С





F488

S4-S5 linker



TRPV1

Membrane protein, 180kDa Polara 300kV – DDD camera (K2) 3D classification Relion

Apoferritin

2020 - 1.22 Å resolution







Apoferritin Soluble protein, 24-fold symmetry, 500 kDa Prototype Cold-FEG, 300kV DDD camera (Falcon4) – Energy filter 3D classification: Relion PDB: 7A4M – EMDB: EMD-11638

β -Galactosidase



Microtubule structure and dynamics

A successful example of an integrative approach to a structural biology problem

1999-2015





References

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