

Central European Institute of Technology BRNO | CZECH REPUBLIC

Image analysis III & 3D Reconstruction

C9940 3-Dimensional Transmission Electron Microscopy S1007 Doing structural biology with the electron microscope

April 11, 2016



FUROPEAN UNION EUROPEAN REGIONAL DEVELOPMENT FUND VESTING IN YOUR FUTURE







Outline

Image analysis III

- More on last week's material
 - Dependence of SNR on \sqrt{N}
 - Oversampling
- Classification

3D Reconstruction

- Principles
- Tomography
- Reference-based alignment
- Common lines
- RCT
- CTF-correction
- 3D classification



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Random walks: Why signal-to-noise improves with \sqrt{N}



The "Drunkard's walk"



Let's conduct an experiment.



The "Drunkard's walk"



We're going to assume that each step is random and independent of previous steps.

The "Drunkard's walk"





The teetotaler's walk





Expectation value



The expected distance that "noise" travels increases with \sqrt{N} . However, it is not as fast as the distance that "signal" travels. Thus, as we collect more data, the SNR increase by N/ $\sqrt{N} = \sqrt{N}$

Random walks: more information





Expectation values and how they related to resolution criteria



Review: How do we evaluate the quality of a reconstruction?

We split the data set into halves and compare them.





Review: Fourier Shell Correlation (FSC)



Properties:

- Fourier terms have amplitude + phase.
- Correlation values range from -1 to +1.
- Noise <u>should</u> give an average of 0.
- The comparison is done as a function of spatial frequency (or "resolution")

Review: Fourier Shell Correlation curve





FSC curve with expectation value of noise





Why does σ vary with spatial frequency?





With small N, behavior is more unpredictable





Review: model bias

N = 1024



N = 2048

original

The model bias can yields false correlations in real space is equivalent to false correlations in Fourier space.



Refinement: classical and "gold standard"



Different resolution criteria



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Sampling: Oversampling an already-sampled image



Shifts: worst-case scenario





Effect of shifts





Oversampling





Worst-case scenario after oversampling





Upscaled







Oversampling: Conclusion

You can do a little better by oversampling. Bammes... Chiu (2012) J. Struct. Biol.



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Classification



Reiteration of the problem

8 classes of faces, 64x64 pixels



With noise added

Average:



Before we can average the data, we first should find homogeneous subsets.



Multivariate data analysis (MDA)

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16



Multivariate data analysis (MDA), or Multivariate statistical analysis (MSA)



Our 16-pixel image can be reorganized into a 16-coordinate vector.


MDA: Reconstituted images

Linear combinations of these images will give us approximations of the images that make up the data.





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Phantom images of worm hemoglobin



MDA of worm hemoglobin

 $-\mathbf{C}_{1}$

 $-C_0$

 $-C_{2}$

Average:





stkreconstituted@1 stkreconstituted@2 stkreconstituted@3 stkreconstituted@4 stkreconstituted@5 stkreconstituted@6 stkreconstituted@7 stkreconstituted@8

 $-C_{2}$

-C₄

 $-C_5$



Classification

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16



How do we categorize/classify the images?



K-means classification



BAD: Some clusters may be overrepresented/underrepresented.













We will note the images that always "travel" together, and will call them a class.

Dendrogram





Dendrogram

OPTIONS	COMMANDS	EDIT INFO	SYSTEM		
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-0.42					
-0.22					
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Hierarchical ascendant classification





Hierarchical Ascendant Classification



All images are represented.

The dendrogram will be too heavily branched to interpret without truncation.



Binary-tree viewer



BAD: Information about the height of the branch is lost.

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How do you go from 2D to 3D?



John O'Brien, 1991, The New Yorker

What information do we need for 3D reconstruction?

1. different orientations

- 2. known orientations
- 3. many particles



What happens when we're missing views?



Baumeister et al. (1999), Trends in Cell Biol., 9: 81-5.

Your sample isn't guaranteed to adopt different orientations, in which case you many need to explicitly tilt the microscope stage. (more later...) What information do we need for 3D reconstruction?

1. different orientations
2. known orientations
3. many particles

I have all of this information. Now what?



There are two general categories of 3D reconstruction

1. Real space

2. Fourier space



Reconstruction in real space



We are going to reconstruct a 2D object from 1D projections. The principle is the similar to, but simpler than, reconstructing a 3D object from 2D projections.







Now, project in several directions





































The reconstruction doesn't agree well with the projections. What can we do?

(one) ANSWER: Simultaneous Iterative Reconstruction Technique



Simultaneous Iterative Reconstruction Technique

The idea:

- You compute re-projections of your model.
- Compare the re-projections to your experimental data.
 - There will be differences.
- You weight the differences by a fudge factor, λ .
- You adjust the model by the difference weighted by λ .
- Repeat.



Simultaneous Iterative Reconstruction Technique



Simultaneous Iterative Reconstruction Technique



Experimental projection



Here, the differences (which will be down-weighted by λ) are the ripples in the background.

If we didn't down-weight by λ , we would overcompensate, and would amplify noise.



Reconstruction in Fourier space





Projection theorem (or Central Section Theorem)

A central section through the 3D Fourier transform is the Fourier transform of the projection in that direction.





Projection theorem (or Central Section Theorem)

The disadvantage is that you have To resample your central sections from polar coordinates to Cartesian space, i.e. interpolate. There are new methods to better Interpolate in Fourier space.



Converting from polar to Cartesian coordinates


Going from 2D to 3D

If you know the orientation angles for each image, you can compute a back-projection.



Adapted from Pawel Penczek



How do we determine the last two Euler angles?



Parameters required for 3D reconstruction



These are determined in 2D. These are determined in 3D.



http://www.wadsworth.org



Going from 2D to 3D

If you know the orientation angles for each image, you can compute a back-projection.



Adapted from Pawel Penczek



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Tomography



We have:

- known orientations
- different views

BUT...



What happens when we image the sample?



Baker et al. (1999) Microbiol. Mol. Biol. Rev. 63: 862

We are destroying the sample as we image it.



Consequences of repeated exposure



- Accumulated beam damage
- If number of views is limited, then distortions

Solution:

If we have many identical molecules, and if we can determine the orientations, we can use one exposure per molecule and use these images in the reconstruction.

"Single-particle reconstruction"



From Ken Downing

If we have many identical molecules, and if we can determine the orientations, we can use one exposure per molecule and use these images in the reconstruction.

BUT:

Unlike in the tomographic case, we don't know how the orientations between the different images are related.



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Reference-based alignment

You will record the direction of projection (the Euler angles), such that if you encounter an experimental image that resembles a reference projection, you will assign that reference projection's Euler angles to the experimental image.

Step 1: Generation of projections of the reference.



From Penczek et al. (1994), Ultramicroscopy 53: 251-70.

Assumption: reference is similar enough to the sample that it can be used to determine orientation.



The model



(The extra features helped determine handedness in noisy reconstructions.)



phi=000 theta=000 psi=000



phi=000 theta=000 psi=000



phi=000 theta=000

psi=000



phi=000 theta=000 psi=000



phi=000 theta=000

psi=000



phi=000 theta=000

psi=000





phi=000 theta=000 psi=000





phi=000 theta=000 psi=000



phi=000 theta=000 psi=000



phi=000 theta=000 psi=000



phi=000 theta=000 psi=000



phi=192 theta=045 psi=000



phi=036 theta=030

psi=000



phi=216 theta=045 psi=000



phi=000 theta=045

psi=000



phi=016 theta=075

psi=000





phi=048 theta=045 psi=000

phi=115

thet a=075

psi=000



phi=072 theta=045 psi=000



phi=131 theta=090 psi=000

Reference-based alignment



From Penczek et al. (1994), Ultramicroscopy 53: 251-70.

Steps:

- 1. Compare the experimental image to all of the reference projections.
- 2. Find the reference projection with which the experimental image matches best.
- 3. Assign the Euler angles of that reference projection to the experimental image.

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Common lines (or Angular Reconstitution)

Summary:

- A central section through the 3D Fourier transform is the Fourier transform of the projection in that direction
- Two central sections will intersect along a line through the origin of the 3D Fourier transform
- With two central sections, there is still one degree of freedom to relate the orientations, but a third projection (i.e., central section) will fix the relative Frank orientations of all three.



Frank, J. (2006) 3D Electron Microscopy of Macromolecular Assemblies



Common lines (or Angular Reconstitution)

Summary:

- A central section through the 3D Fourier transform is the Fourier transform of the projection in that direction
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From Steve Fuller



Common lines: Problems

- Noise can lead to incorrect angles
 - Symmetry helps
- Handedness cannot be determined without additional information
 - Tilting
 - α-helices
- Assumes conformational homogeneity



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Random-conical tilt: Determination of Euler angles



This scenario describes a worst case, when there is exactly one orientation in the 0° image. Since the in-plane angle varies, in the tilted image, we have different views available.

From Nicolas Boisset

Random-conical tilt: Geometry

Two images are taken: one at 0° and one tilted at an angle of 45°.



Radermacher, M., Wagenknecht, T., Verschoor, A. & Frank, J. Three-dimensional reconstruction from a singleexposure, random conical tilt series applied to the 50S ribosomal subunit of *Escherichia coli*. J Microsc **146**, 113-36 (1987).

From Nicolas Boisset



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phi=000	phi=000	phi=000
theta=000	theta=000	theta=000
psi=000	psi=000	psi=000



phi=000	phi=048	phi=072
thet a=001	theta=001	thet a=001
psi=000	psi=000	psi=000
phi=192	phi=216	phi=240
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phi=000	phi=048	phi=072
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psi=000	psi=000	psi=000
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phi=192	phi=216	phi=240
phi=192 thet a=045	phi=216 thet a=045	phi=240 thet a=045



One problem though:

We can't tilt the stage all the way to 90 degrees.



Review:

Projection theorem





Random-conical tilt: The "missing cone"

Representation of the distribution of views, if we display a plane perpendicular to each projection direction

The missing information, in the shape of a cone, elongates features in the direction of the cone's axis.



From Nicolas Boisset



Random-conical tilt: Filling the missing cone

If there are multiple preferred orientations, or if there is symmetry that fills the missing cone, you can cover all orientations.



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Phantom images of worm hemoglobin



We compute a separate reconstruction for each class



<u>IF</u> the classes simply correspond to different orientations, you can combine them, and boost the signal-to-noise.



Helicase G40P



If the classes correspond to different conformations, then you have to keep them as separate reconstructions.



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More properties of Fourier transforms: Convolutions



Why might two images in a data set look different?

- different sample
 better
- different magnification
- different illumination
- different orientations
 de
- different defocus
 CTF correction
- different
 Classification
 conformations

- better biochemistry
- better microscopy
- normalization
- determine angles



Convolution of a molecule with a lattice generates a crystal. Notation: $f(x) \cdot g(x)$

Adapted from David DeRosier



lattice: f(x)

Set a molecule down at every lattice point.




Convolution in real life

Notation: $f(x) \cdot g(x)$



lattice: *f(x)* http://www.photos-public-domain.com



Molecule: g(x) http://en.wikipedia.org

http://www.symbolicmessengers.com

Set a molecule down at every lattice point.



Cross-correlation vs. convolution

Complex conjugate: If a Fourier coefficient F(X) has the form: a + biThe complex conjugate $F^*(X)$ has the form: a - bi

Cross-correlation: $F^*(X) G(X)$

Convolution: F(X) G(X)

Remember: f(x), g(x) are real-space functions F(X), G(X) are Fourier-space functions



original







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f(x)



F(X)



g(x)



G(X)



 $f(x) \cdot g(x)$





Point spread function



An ideal point spread function would be an infinitely-sharp point.



Red: Power-spectrum profile calculated from experimental image Green: Fitted, theoretical power-spectrum profile Blue: Phase-only correction profile



Defocus groups: CTF correction in 3D

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Reference-based Reconstruction



CTF-correction of micrographs in 2D





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- different defocus
- different conformations

- better biochemistry
- better microscopy
- normalization
- determine angles
- CTF correction
- Classification



Classification: Reference-based classification vs. Maximum likelihood (ML3D)

Reference-based classification:			ML3D	
• Po kr	ossible conformations must be nown.	•	Possible conformations are not known.	
• TI (s fro va	he combination of parameters shift, rotation, class) is chosen om the highest correlation alue.	•	The probability of the occurrence of the parameters (shift, rotation, class) is maximized.	
• P	ossible reference bias	•	Random, data-dependent	

RELION is a variation of maximum likelihood.



Seeding ML3D classification

We split the data set into *K* classes at random.



There will be slight differences in the reconstructions. We will iteratively maximize the likelihood of a particle belonging to a particular class.



Thank you for your attention



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