# COCITEC 

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

March 23, 2015


## Outline

## Image analysis III

- Still more Fourier transforms
- Convolution
- Step function
- Power spectrum
- Friedel's Law
- More orientation alignment
- More interpolation
- Classification


## 3D Reconstruction

- Principles
- Reference-based alignment
- RCT

Current events: Convolutions

## Convolution of a molecule with a lattice generates a crystal. <br> Notation: $\mathrm{f}(\mathrm{x})^{*} \mid(\mathrm{x})$

From David DeRosier

lattice $=1(x)$


Set a molecule down at every lattice point.


Molecule $=f(x)$

## Convolution of a molecule with a lattice generates a crystal. <br> Notation: $\mathrm{f}(\mathrm{x})^{*} \mathrm{I}(\mathrm{x})$


lattice $=I(x)$
(http://www.photos-public-domain.com)

http://www.symbolicmessengers.com

Set a molecule down at every lattice point.

Molecule $=f(x)$
http://en.wikipedia.org

## Cross-correlation vs. convolution

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

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

Convolution: $F(X) G(X)$


## 1D profile




2D power spectrum $G(X)$


## Point spread function


$g(x)$
zoomed
An ideal point spread function would be an infinitely-sharp point.

## Defocus groups

## Reference-based Reconstruction

N Micrographs


## Defocus groups



Step function revisited

## Fourier transforms: plot of step function

The higher the spatial frequencies (i.e., higher resolution) that are included, the more faithful the representation of the original function will be.


The power spectrum is the a real (as opposed to complex) map of the amplitudes of the Fourier transform


Image $f(x)$

F.T. $F^{*}(X)$ (complex conjugate)


Image $g(x)$

F.T. $G(X)$


CCF

The position of the peak gives us the shifts that give the best match, e.g., (8,-6). It's more difficult to plot a 2D F.T. showing both amplitude and phase.

## Fourier transform of a 2D crystal

| h | k | Amp | Phase |
| :---: | :---: | :---: | :---: |
| 0 | 0 | 500 | 0 |
| 1 | -1 | 40 | 45 |
| 1 | 0 | 50 | 5 |
| 1 | 1 | 30 | 5 |
| 2 | -2 | 2 | 54 |
| 2 | -1 | 4 | 57 |

## QUESTION:

Why did I not list the Fourier data where h was negative?

| h | k | Amp | Phase |
| :---: | :---: | :---: | :---: |
| 0 | 0 | 500 | 0 |
| 1 | -1 | 40 | 45 |
| 1 | 0 | 50 | 5 |
| 1 | 1 | 30 | 5 |
| 2 | -2 | 2 | 54 |
| 2 | -1 | 4 | 57 |

## Friedel's Law

If the complex part of $f(x)$ is zero, then

$$
\begin{gathered}
F(-X)=F^{*}(X) \\
\text { where * indicates the complex conjugate. }
\end{gathered}
$$

USE: Thus, centrosymmetrically related reflections have the same amplitude but opposite phases (Friedel's law).

When calculating a transform of an image, one only has to calculate half of it. The other half is related by Friedel's law.

From David DeRosier

## 2D Fourier transform of a helix




## More orientational alignment

## Orientation alignment



Image 1


Image 2

We take a series of rings from each image, unravel them, and compute a series of 1D cross-correlation functions.

Shifts along these unraveled CCFs is equivalent to a rotation in Cartesian space.

## Orientation alignment



Image 1

## radius 1 <br> radius 2 radius 3 360



Image 2

Reference image


## Orientation alignment



Image 1

radius 1 radius 2 radius 3 radius 4

Polar representation

## Orientation alignment


radius 1
radius 2
radius 3
radius 4
360
0




[^0]
## Orientation alignment: After rotation


radius 1
radius 2
radius 3
radius 4





[^1][^2]Another strategy for translation and orientation alignment

## Translational and orientation alignment are interdependent



Set of all shifts of up to 1 pixel
Set of all new shifts of up to 2 pixels Shifts of ( $0,+/-1,+/-2$ ) pixels results in 25 orientation searches.

The power spectrum is translationally invariant. If we shift the object in real space, the power spectrum is unchanged.

## Cross-correlation function (CCF)



The position of the peak gives us the shifts that give the best match, e.g., $(8,-6)$.

## Cross-correlation function (CCF)



Problems:

1. The power spectrum of a roughly round object is roughly round.
2. The amplitudes fall off quickly, so you don't have many rings of useful data.

## More interpolation

Bammes... Chiu (2012) J. Struct. Biol.



Suppose we shift the image in $x \& y$.
The new pixels will be weighted averages of the old pixels.

Effect of shifts

$\Delta x=\Delta y=0.25 p x$

$\Delta x=\Delta y=0.05 p x$

$\Delta x=\Delta y=0.30 p x$


$\Delta x=\Delta y=0.35 p x$

$\Delta x=\Delta y=0.40 p x$

$\Delta x=\Delta y=0.45 p x$



## Questions

1) If the pixel size is $3 \AA / p x$, what is the Nyquist frequency?

- ANSWER: 1/6A

2) If we oversample/upscale the image by a factor of 1.5 X , what is the new pixel size?

- ANSWER: 2 Å/px

3) What will be the new Nyquist frequency in the oversampled image?

- ANSWER: 1/4Å

White noise

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Power spectrum


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## Conclusion: <br> You can do a little better by oversampling. <br> Bammes... Chiu (2012) J. Struct. Biol.

## Classification

## Multivariate data analysis (MDA)



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

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

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

## MDA: An example

## 8 classes of faces, $64 \times 64$ pixels



With noise added

## Average:



From http://spider.wadsworth.org/spider_doc/spider/docs/techs/classification/tutorial.html

## Principal component analysis (PCA) or Correspondence analysis (CA)

- For a 4096-pixel image, we will have a $4096 \times 4096$ covariance matrix.
- Row-reduction of the covariance matrix gives us "eigenvectors."
- The eigenvectors describe correlated variations in the data.
- The eigenvectors have 64 elements and can be converted back into images, called "eigenimages."
- The finst eigenvectors will acocuint for the most variation. The later eigenvectors may only describe noise.
- L inear combinations of these images will give us approximations of the classes that make up the data.


Eigenimages

## Reconstituted images

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


Average Eigenimage \#1 Eigenimage \#2 Eigenimage \#3

## Another example：worm hemoglobin

Display Select class 1 start key： 1

| ＊ | \％ | ＊ | ＊ | 3 | （3） | $\%$ | 4 | ＊ | 88 | － | ， |
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PCA of worm hemoglobin

## Average:



## 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



Diday's method of moving centers

Factor 1 vs 2


싱․

Diday's method of moving centers


Diday's method of moving centers


Diday's method of moving centers


Dendrogram

CLA/dendrogram.ps


## Dendrogram



## Hierarchical Ascendant Classification

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



## Hierarchical Ascendant Classification



All images are represented.
The dendrogram will be too heavily branched to interpret without truncation.

## Binary-tree viewer


\& СЕ।TEС

3D Reconstruction

## What information do we need for 3D reconstruction?

## 1. different orientations <br> 2. known orientations <br> 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.

## Why do we need orientation?

aligned images 1-4 of 4096 total

unaligned images 1-4 of 4096 total
This is a simple 2D case, but the effects are analogous in 3D.

## What happens as we include more particles?



Signal-to-noise ratio increases with $\sqrt{ } n$

## What information do we need for 3D reconstruction?

## 1. different orientations <br> 2. known orientations <br> 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.

Projection of our 2D object



## Reconstruction is the inversion of projection



## Reconstruction is the inversion of projection



Reconstruction is the inversion of projection


$$
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$$

## Reconstruction is the inversion of projection



Reconstruction is the inversion of projection


## What happens when we're missing views?



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

## Simultaneous Iterative Reconstruction Technique



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

(one) ANSWER:<br>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, $\lambda$.
- You adjust the model by the difference weighted by $\lambda$.
- Repeat.


## Simultaneous Iterative Reconstruction Technique



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

If we didn't down-weight by $\lambda$, we would over compensate, 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.

Reference-based alignment (or projection-matching)

## 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.)

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## Reference-based alignment

Stack of projections
Stack of rotational CCF's


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.

Random conical tilt




## Binary-tree viewer


\& СЕ।TEС

## Random-conical tilt:

Filling the missing cone
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.


From Nicolas Boisset

Top view


## Side view



3D classification

Classification: Multi-reference alignment vs. Maximum likelihood (ML3D)

Multi-reference alignment: ML3D

- Possible conformations must be known.
- The combination of parameters (shift, rotation, class) is chosen from the highest correlation value.
- Possible conformations are not known.
- The probability of the occurrence of the parameters (shift, rotation, class) is maximized.


## 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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 Development for Innovation


## There isn't an unambiguous 3D structure if there's only one



John O'Brien, 1991, The New
Yorker

## What information do we need for 3D reconstruction?

## 1. different orientations <br> 2. known orientations <br> 3. many particles <br> 4. identical particles


[^0]:    356.141, -2.50024

[^1]:    374.951, 4.53721

[^2]:    372.357, -3.21418

