



CEITEC

Central European Institute of Technology  
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MUNI

FB820

Lecture 6

3DEM methods

*Jiri Novacek*

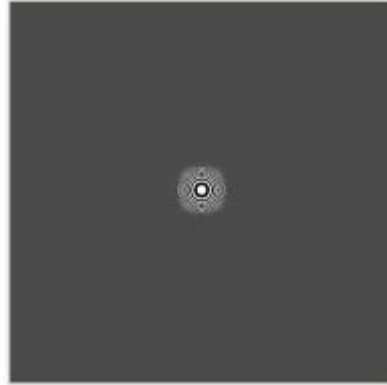
# Content

- image formation, CTF, image filtering
- image alignment in 2D
- 3D reconstruction
- common lines
- random conical tilt

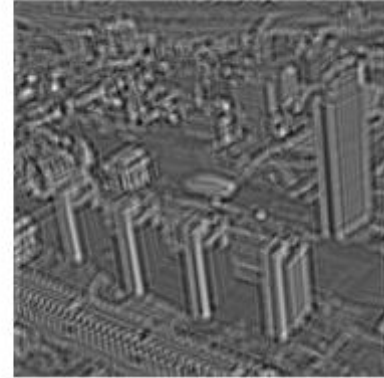
# Image formation



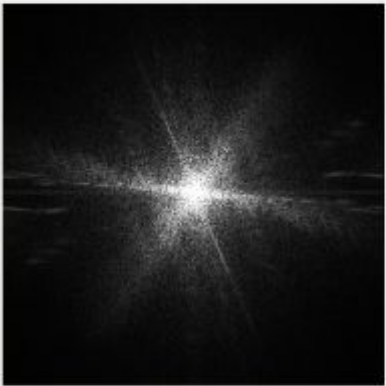
$f(x)$



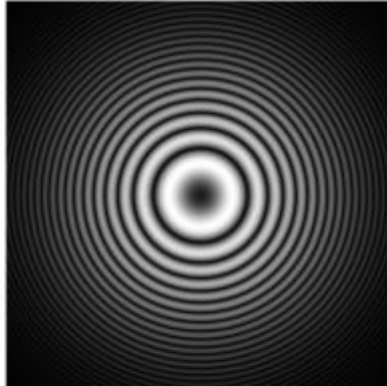
$g(x)$



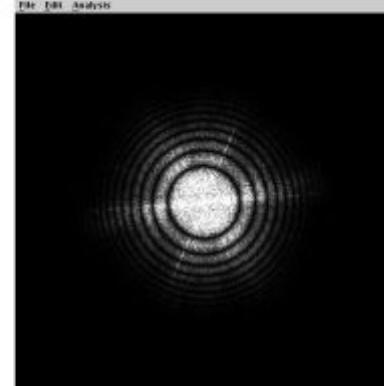
$f(x) \bullet g(x)$



$F(X)$

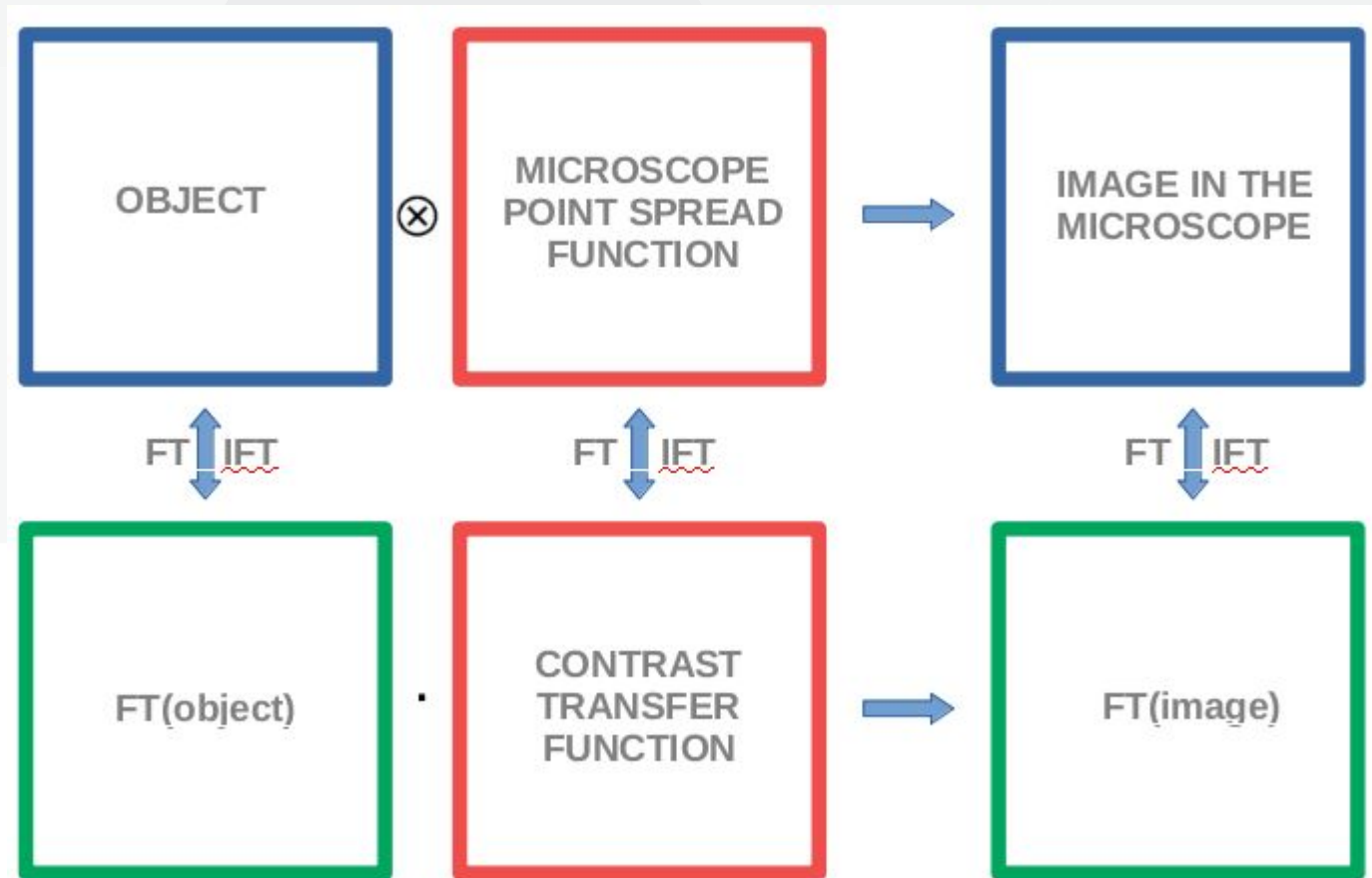


$G(X)$

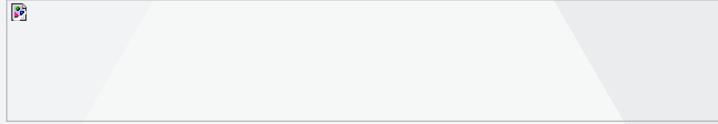
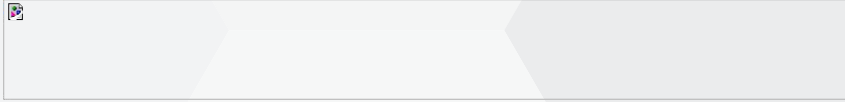


$F(X) G(X)$

# Image formation



# Contrast transfer function



A – amplitude contrast

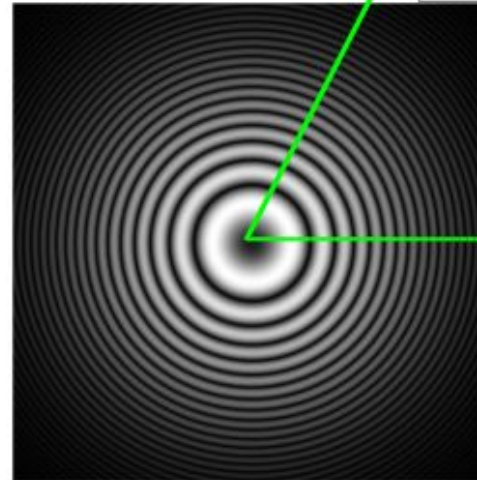
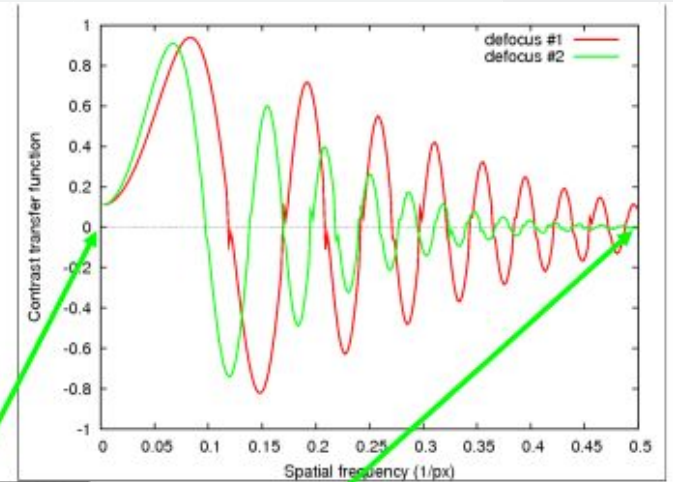
s – spatial frequency

C<sub>s</sub> – spherical aberration

$\lambda$  – electron wavelength

z – defocus

1D profile



2D power spectrum  
 $G(X)$

# Contrast transfer function

Envelope function

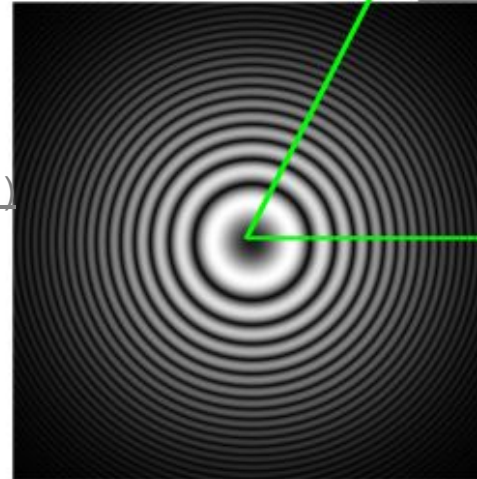
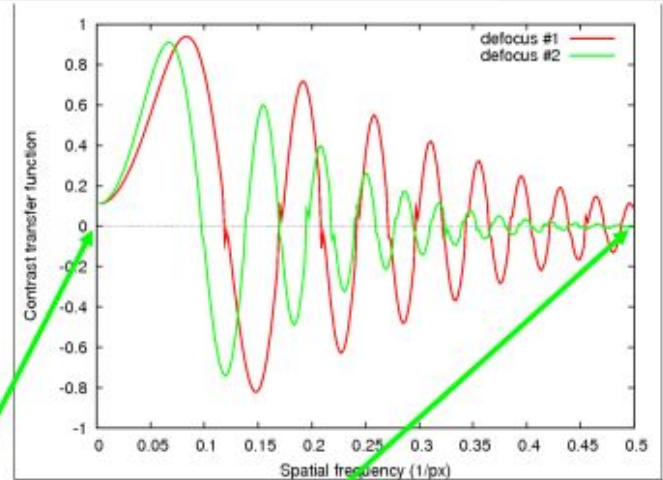
- Finite source size

- Energy spread (defocus)

- MTF of the camera

- Generic envelope (drift, charging, multiple scattering)

1D profile



2D power spectrum  
 $G(X)$

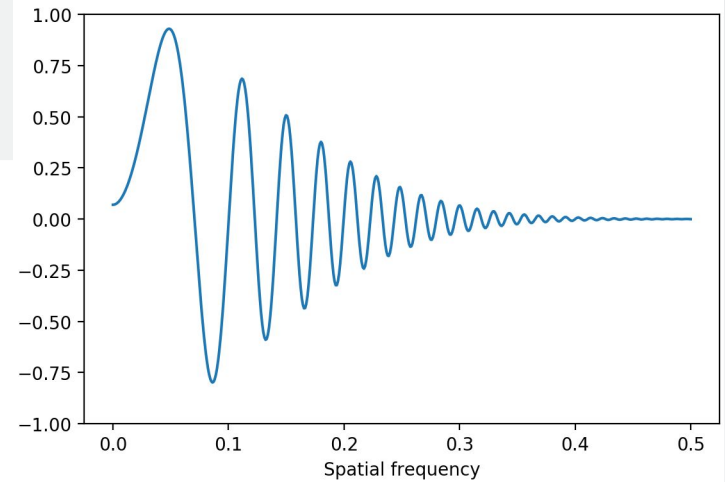
# Contrast transfer function

Envelope function

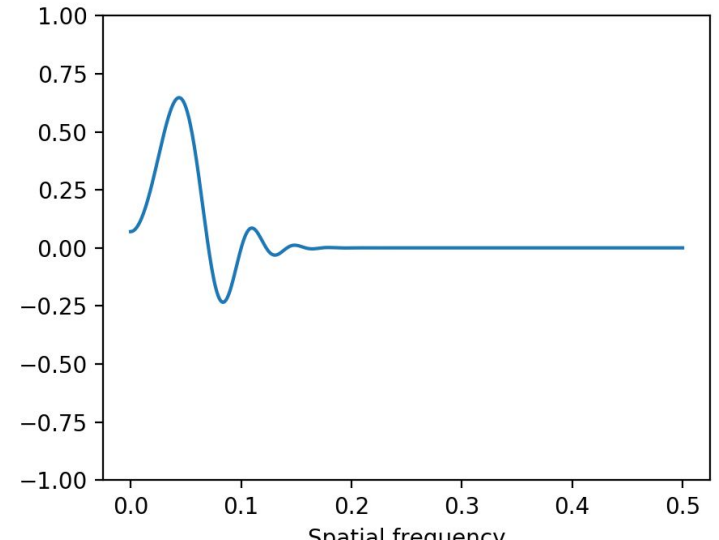
$$I(\mathbf{k}) = \underbrace{E_{pc}(k)E_{es}(k)E_f(k)E_g(k)H(k)}_{e^{-Bk^2}}\Phi(\mathbf{k}) + N(\mathbf{k}).$$

$$e^{-Bk^2}$$

kV=300,ac=0.07,cs=2.7,z=-1,apix=1,B=30

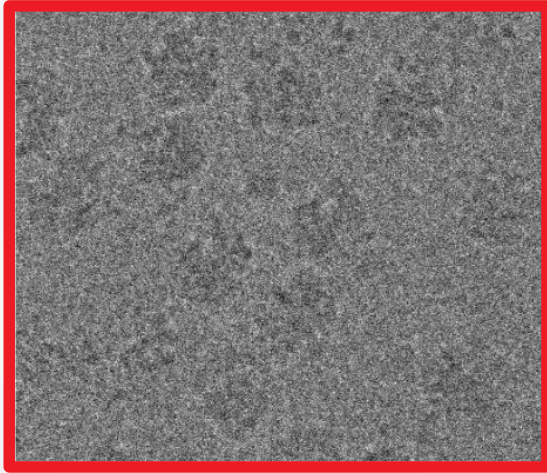


kV=300,ac=0.07,cs=2.7,z=-1,apix=1,B=300

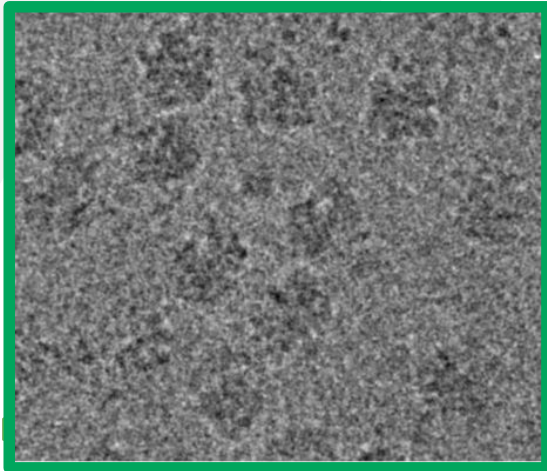




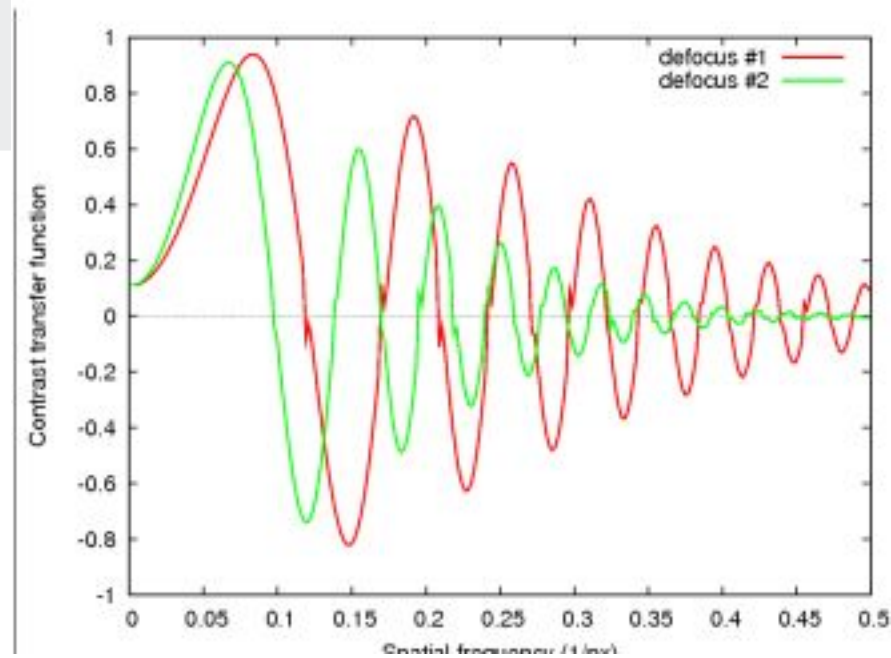
# Contrast transfer function



Low defocus



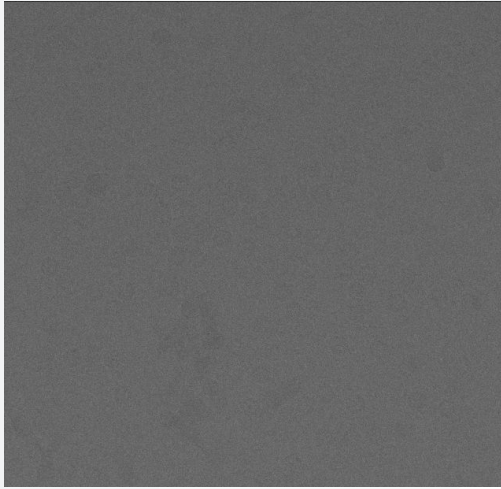
High defocus



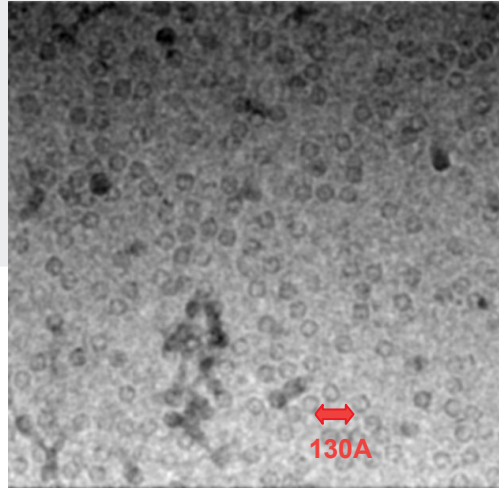


# Image filtering

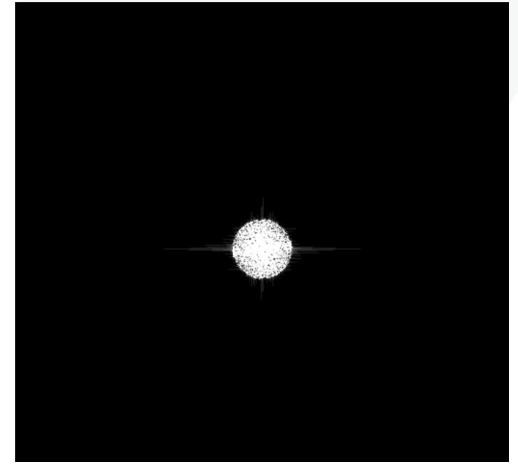
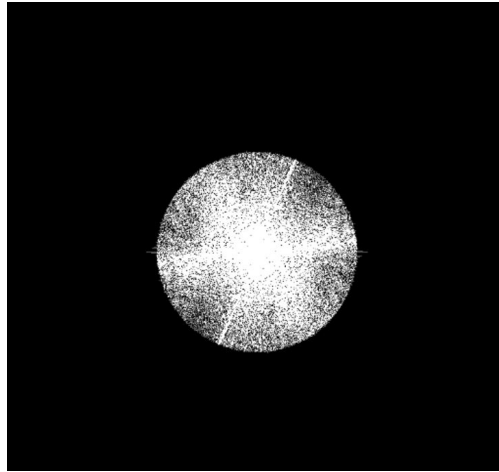
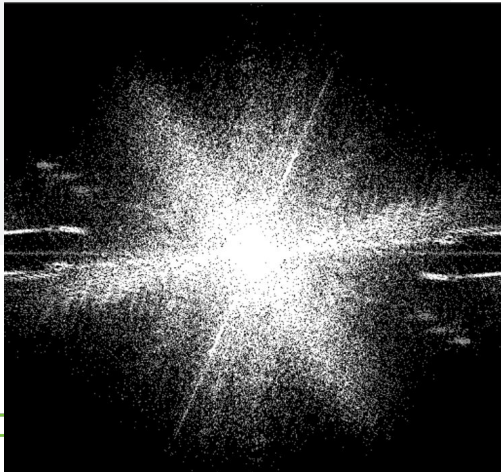
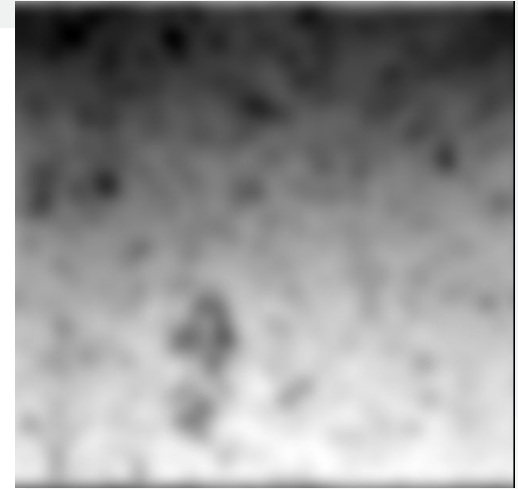
unfiltered image



lowpass filtered (50A)

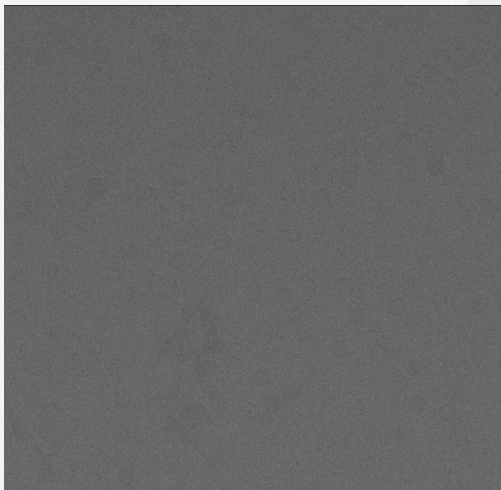


lowpass filtered (250A)

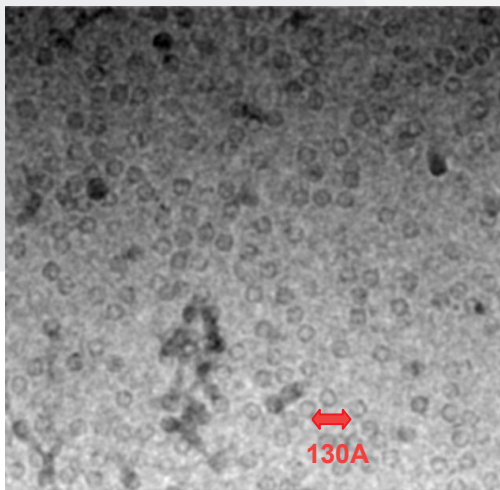


# Image filtering

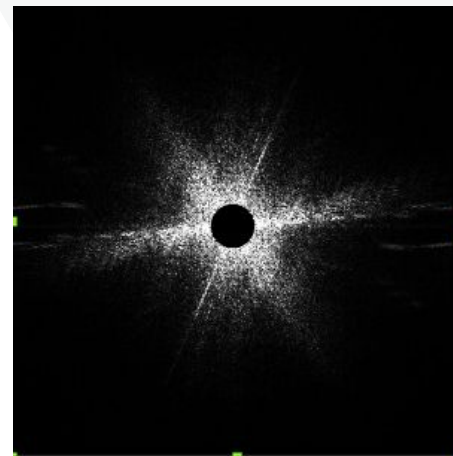
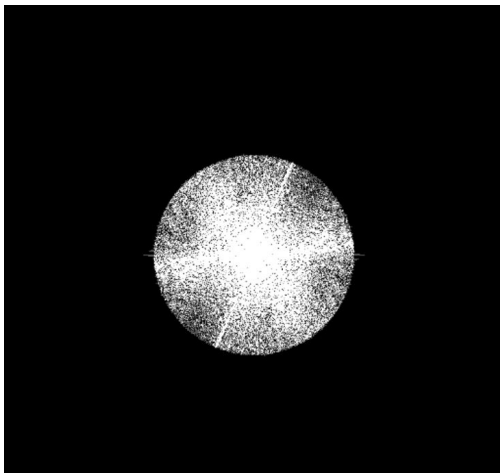
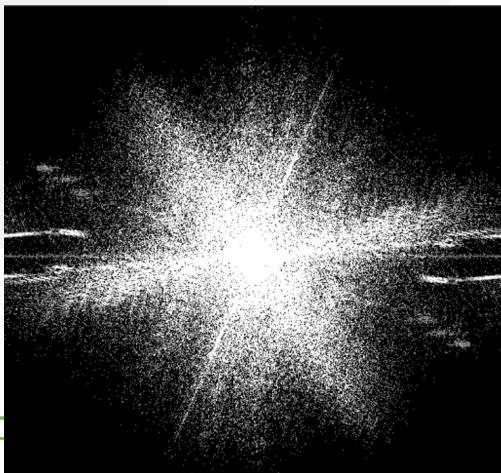
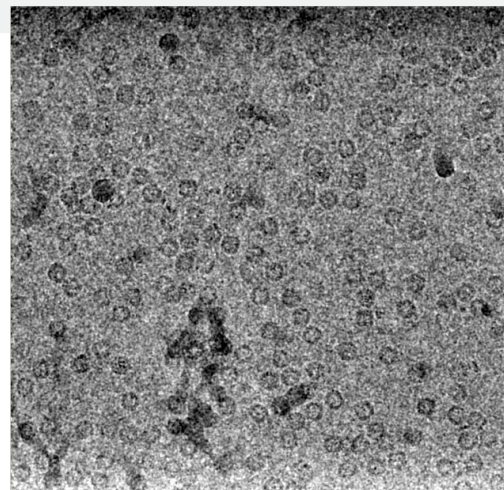
unfiltered image



lowpass filtered (50A)

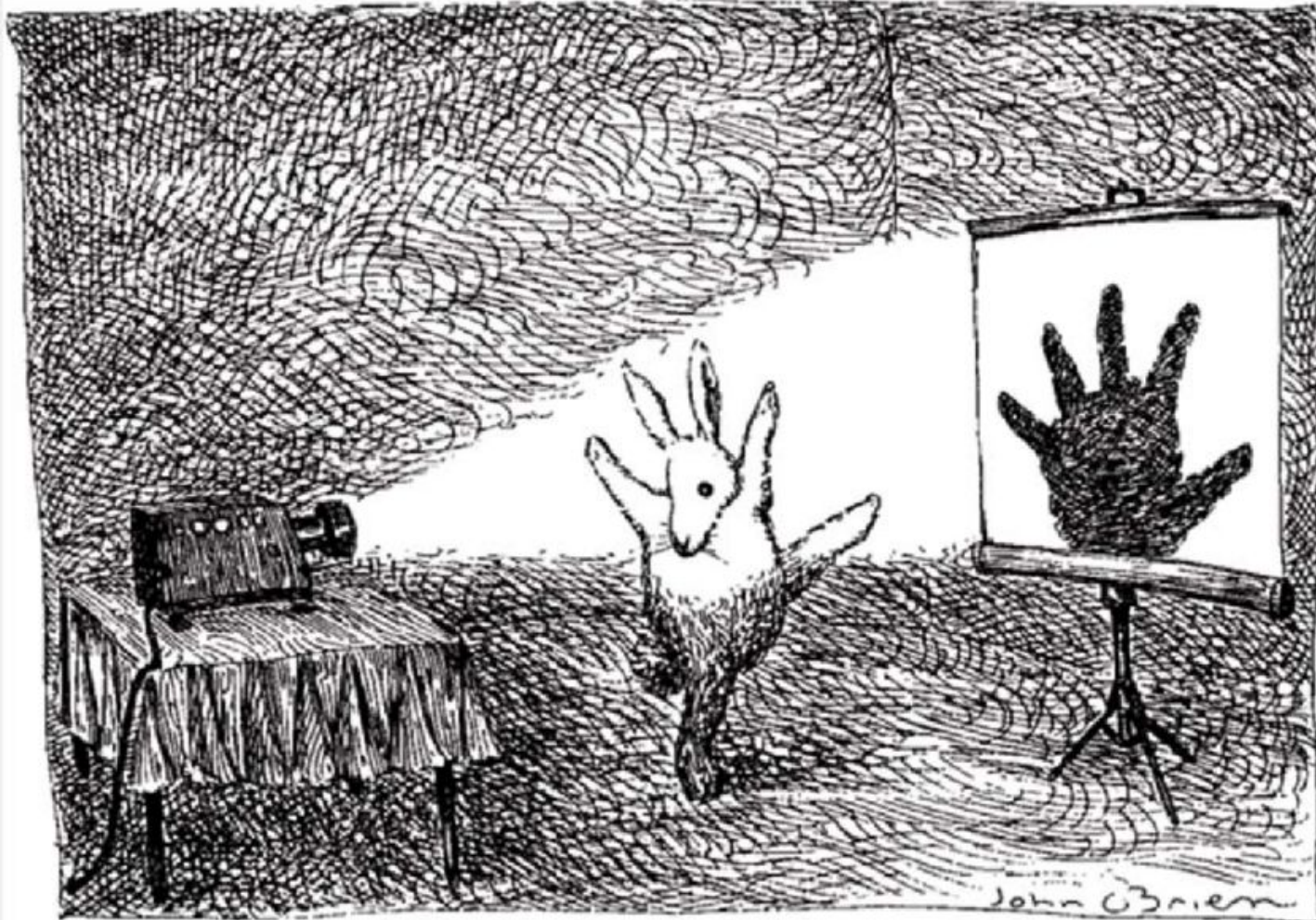


bandpass filtered (1000,10A)



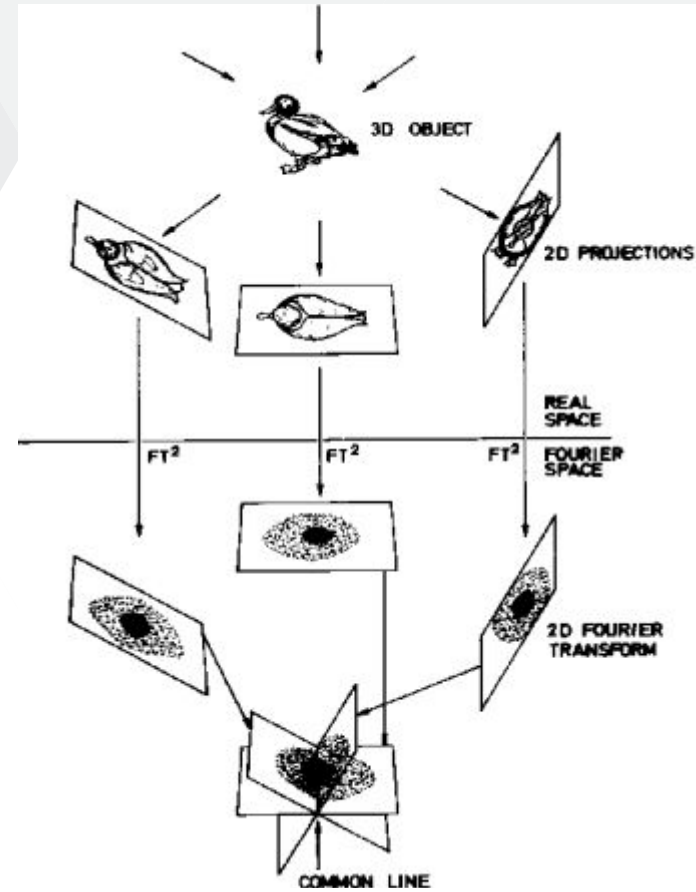
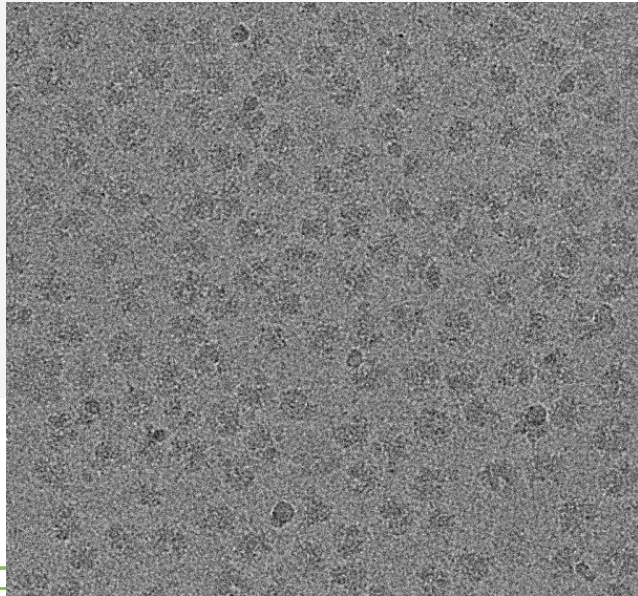
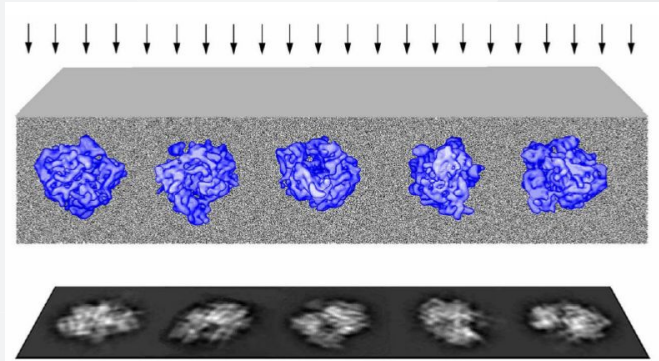


# Projection theorem



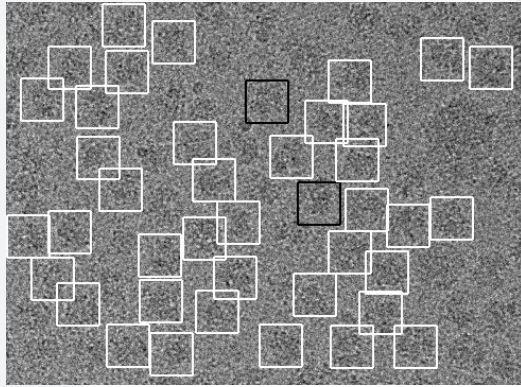
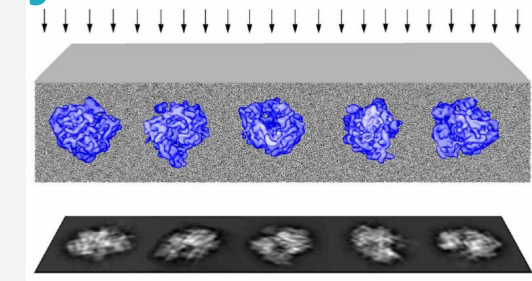
John O'Brien (1991). The New Yorker

# Projection theorem



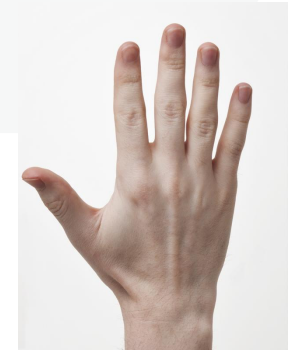
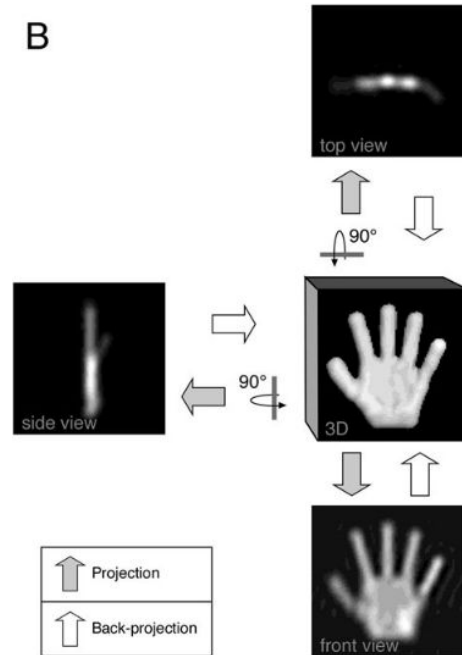
The 2D Fourier transform of the projection of a 3D density is a central section of the 3D Fourier transform of the density, perpendicular to the direction of projection.

# cryo-TEM imaging



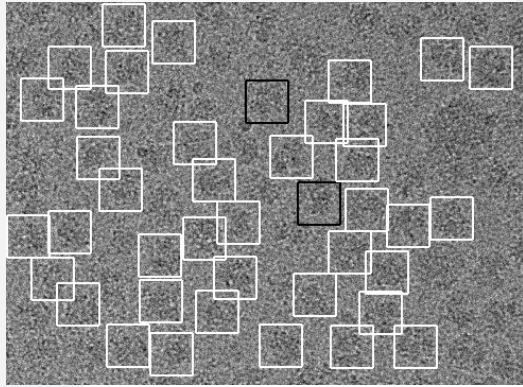
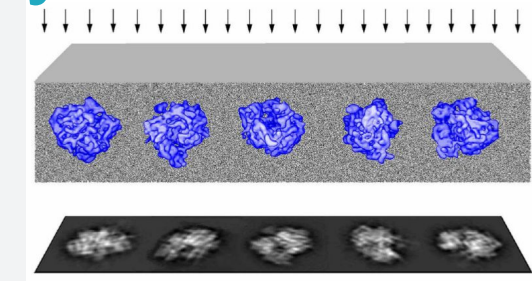
- 2D projections of an 3D object (handedness)
- high noise level (low sensitivity)
- convolution with microscope point spread functions

B



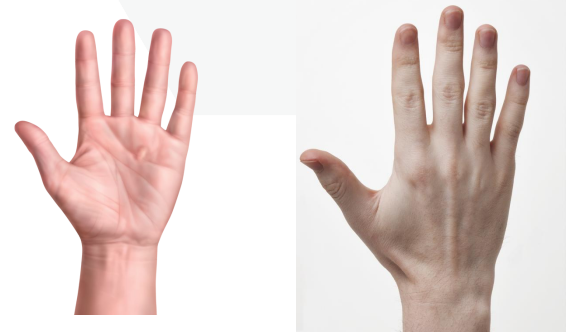
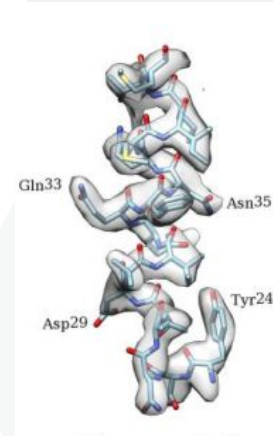
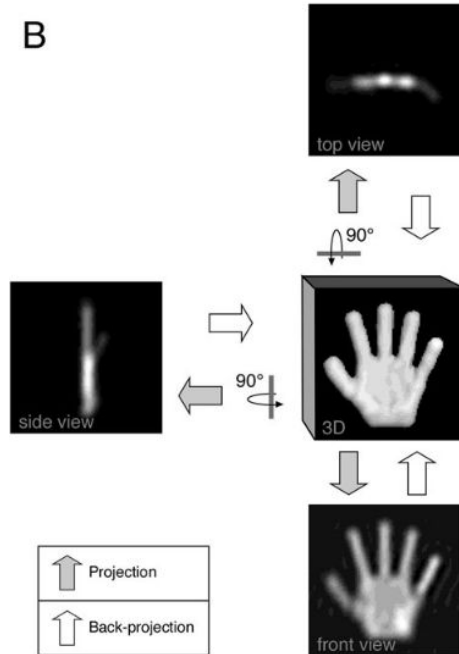


# cryo-TEM imaging



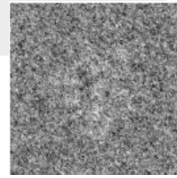
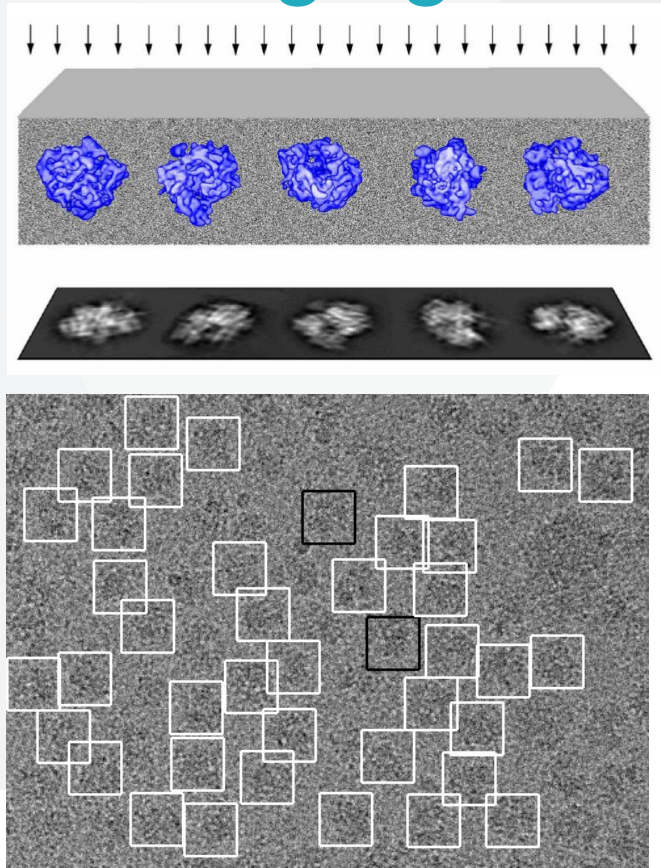
- 2D projections of an 3D object (handedness)
- high noise level (low sensitivity)
- convolution with microscope point spread functions

B



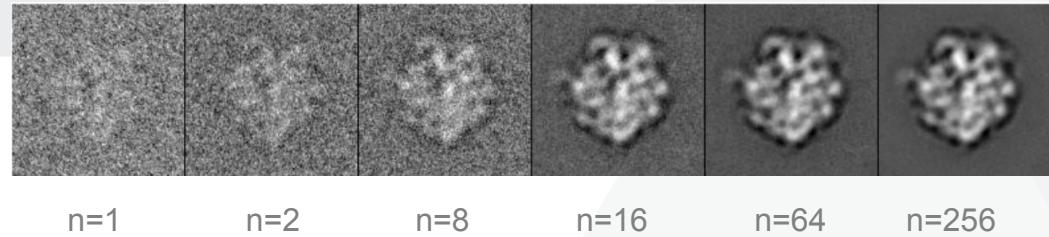
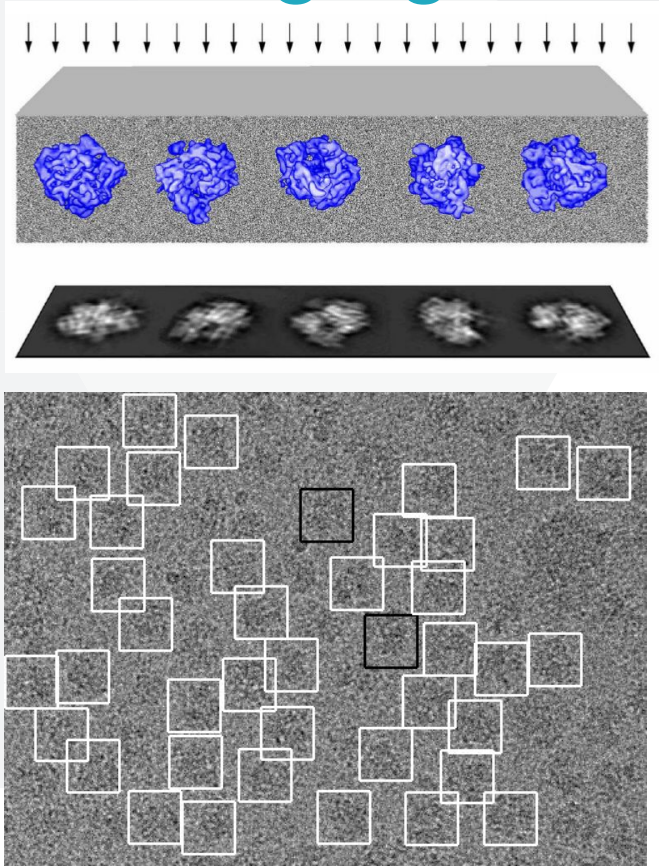


# Averaging



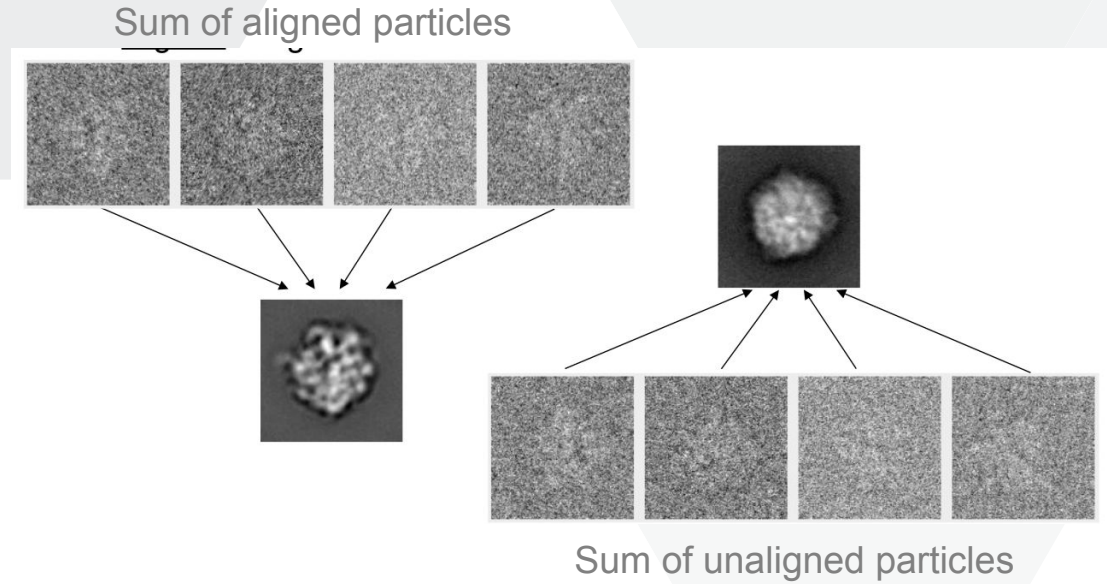
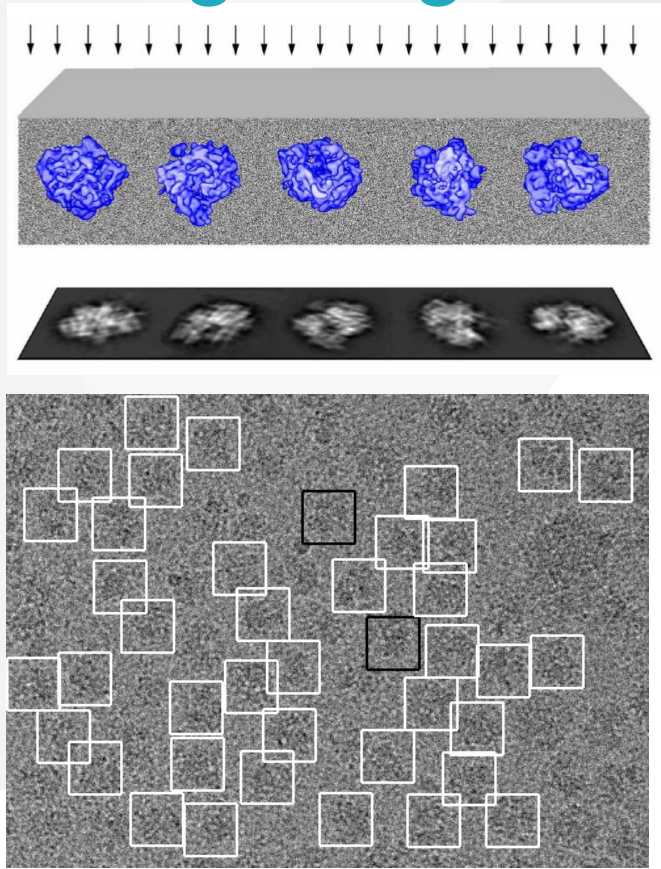
n=1

# Averaging



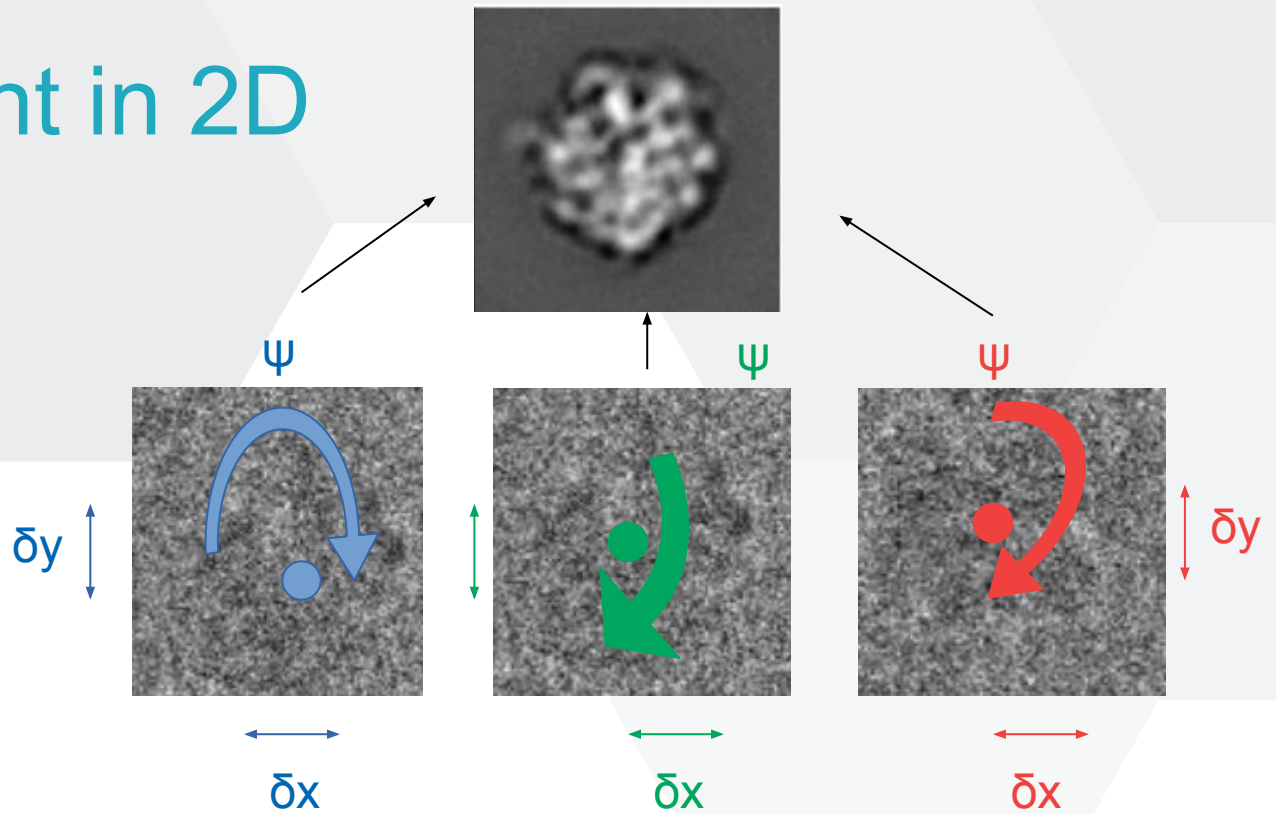
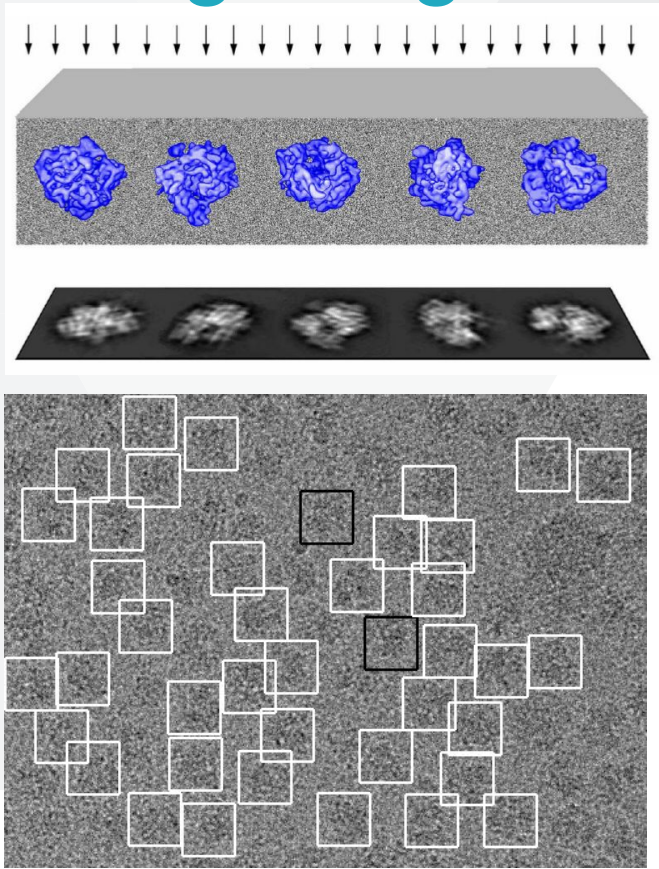
Signal to noise ratio increases with square-root of  $n$

# Image alignment in 2D





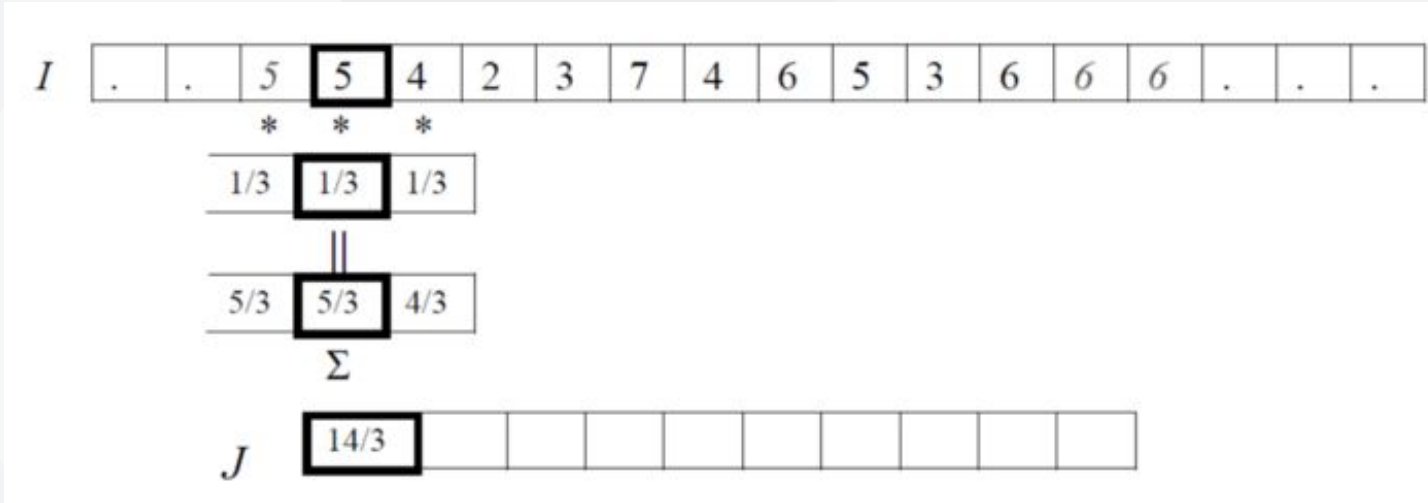
# Image alignment in 2D



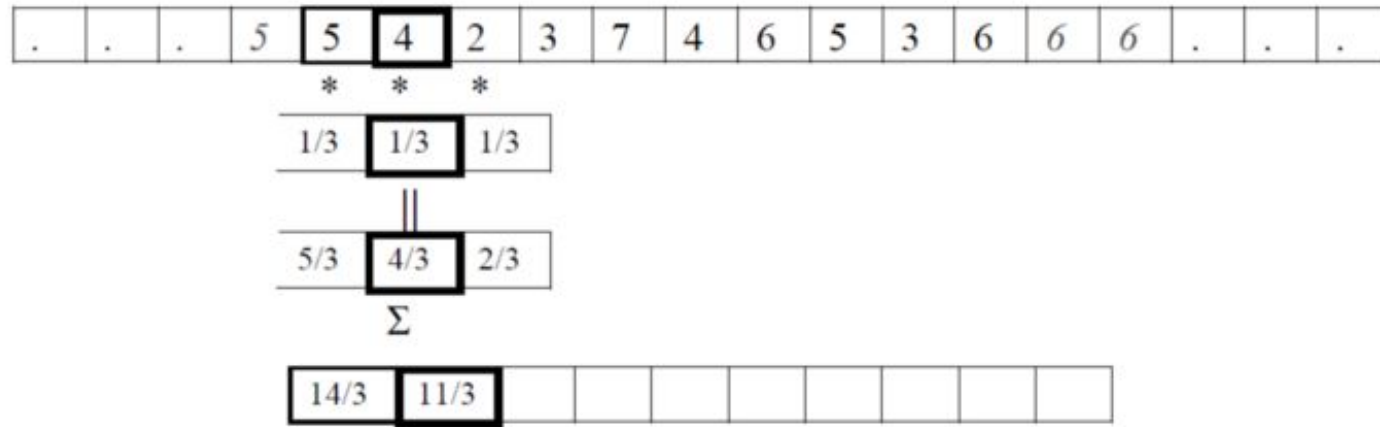
In order to align the particles in 2D, we need to determine three parameters:

- two translational
- one rotational (one of the Euler angles)

# Cross correlation function in 1D



# Cross correlation function in 1D

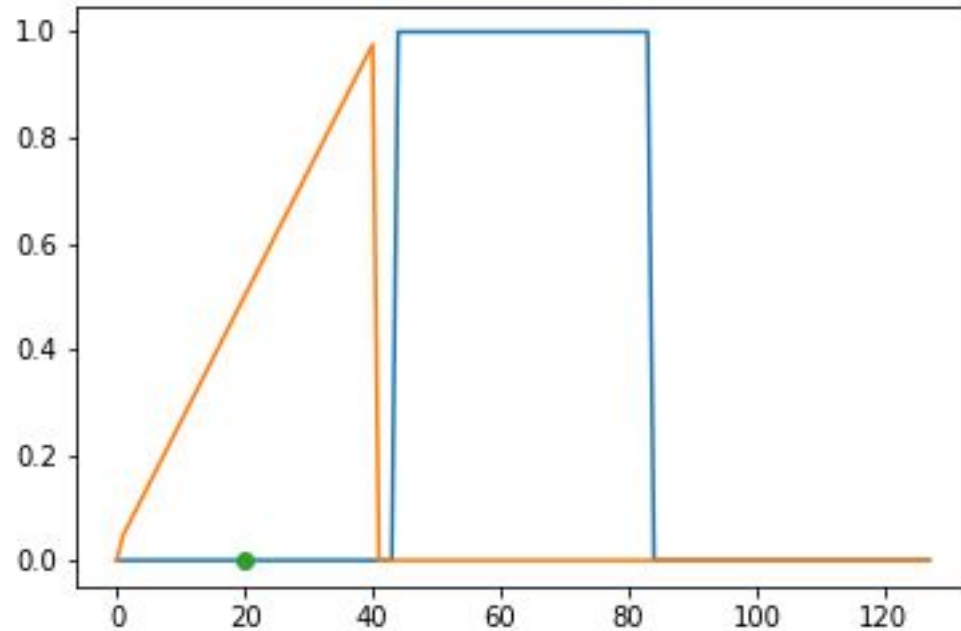


$$F \circ I(x) = \sum_{i=-N}^N F(i)I(x+i)$$

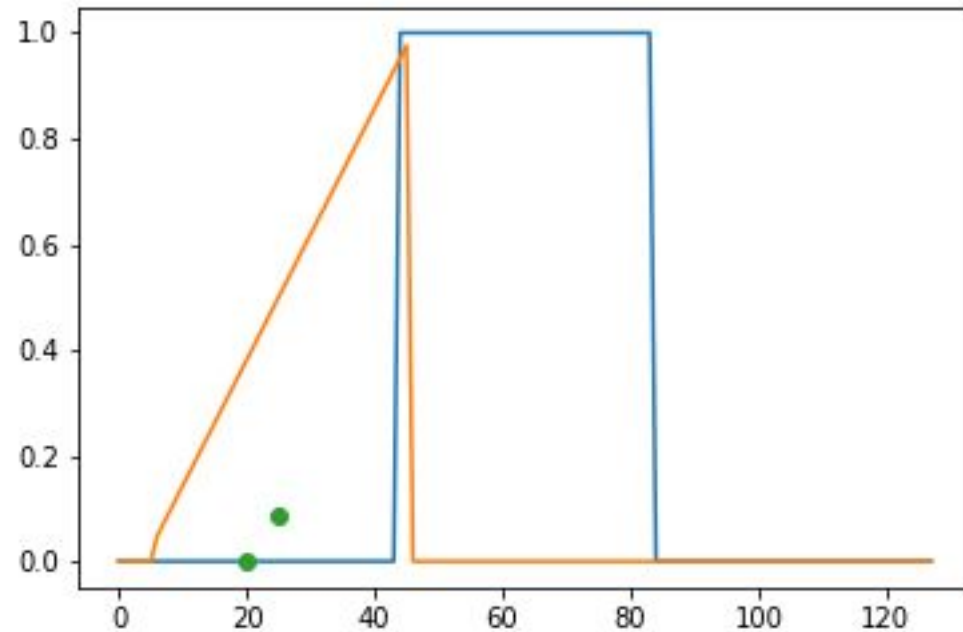


# Cross correlation

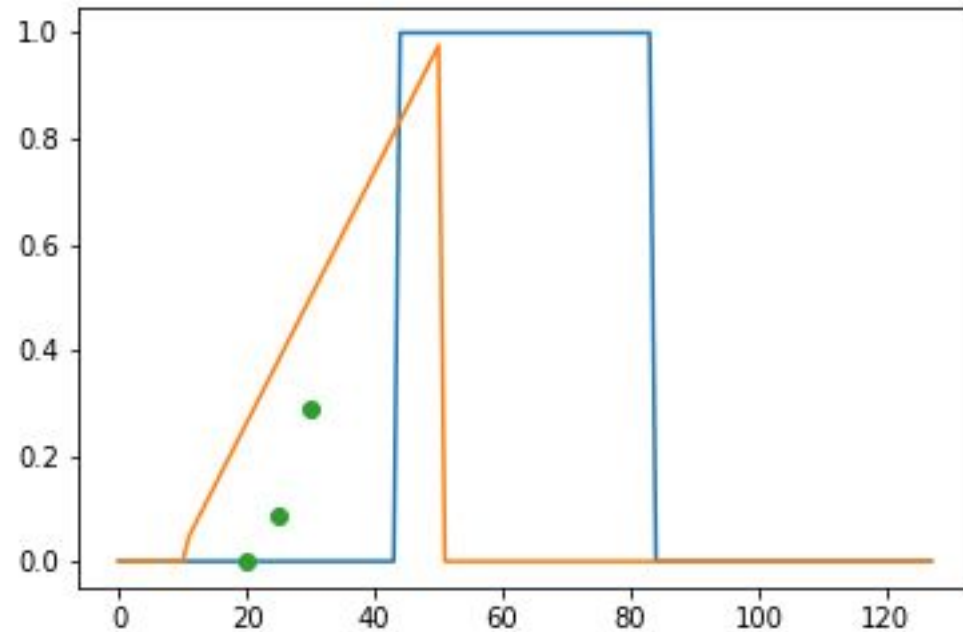
- measure of similarity of two data series as a function of displacement of these functions
- in 2D optimal overlay of two images
- normalized cross-correlation –  $ccc = \langle -1, 1 \rangle$



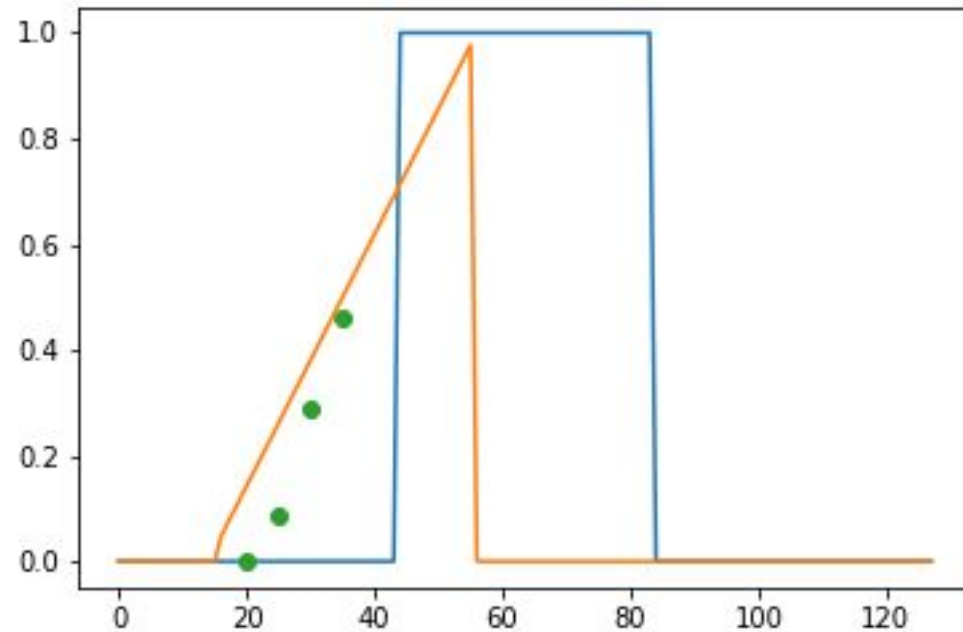
# Cross correlation function in 1D



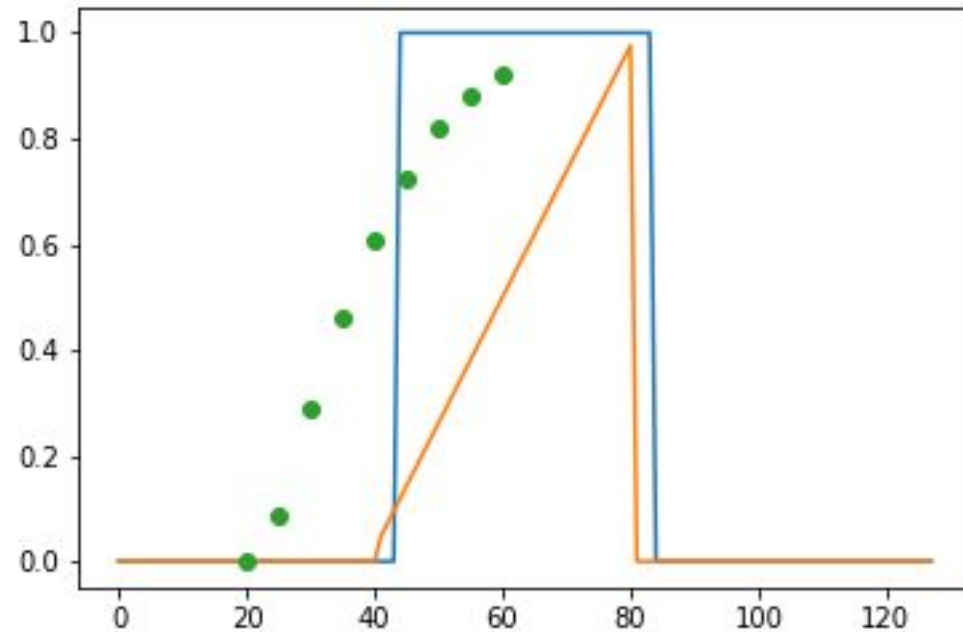
# Cross correlation function in 1D



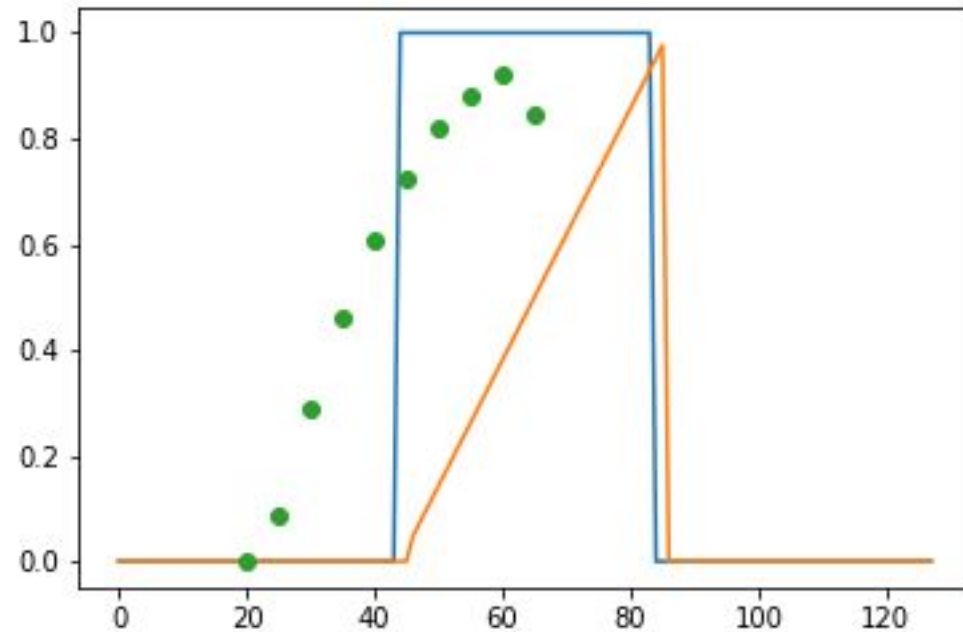
# Cross correlation function in 1D



# Cross correlation function in 1D

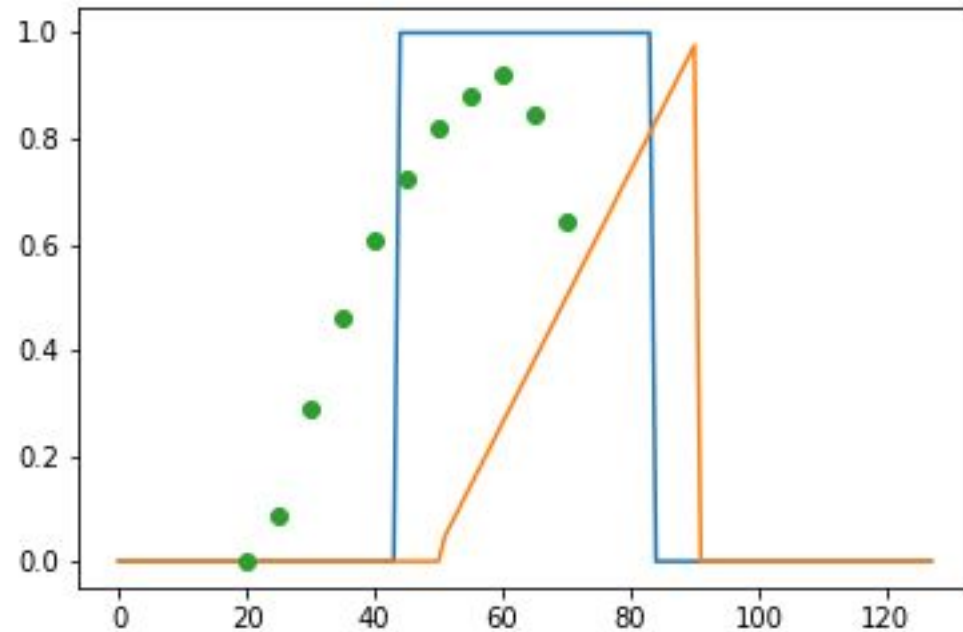


# Cross correlation function in 1D

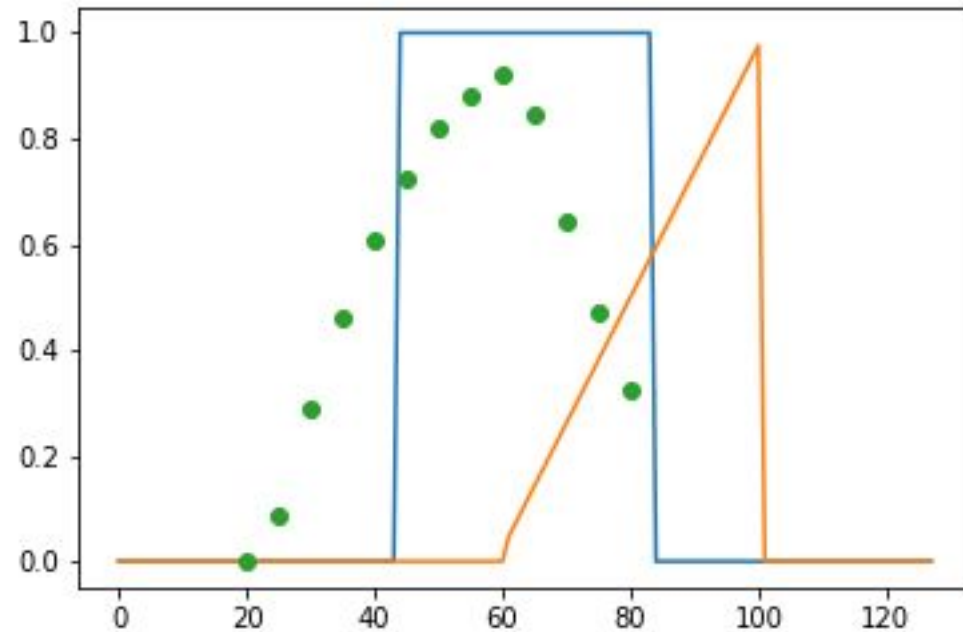




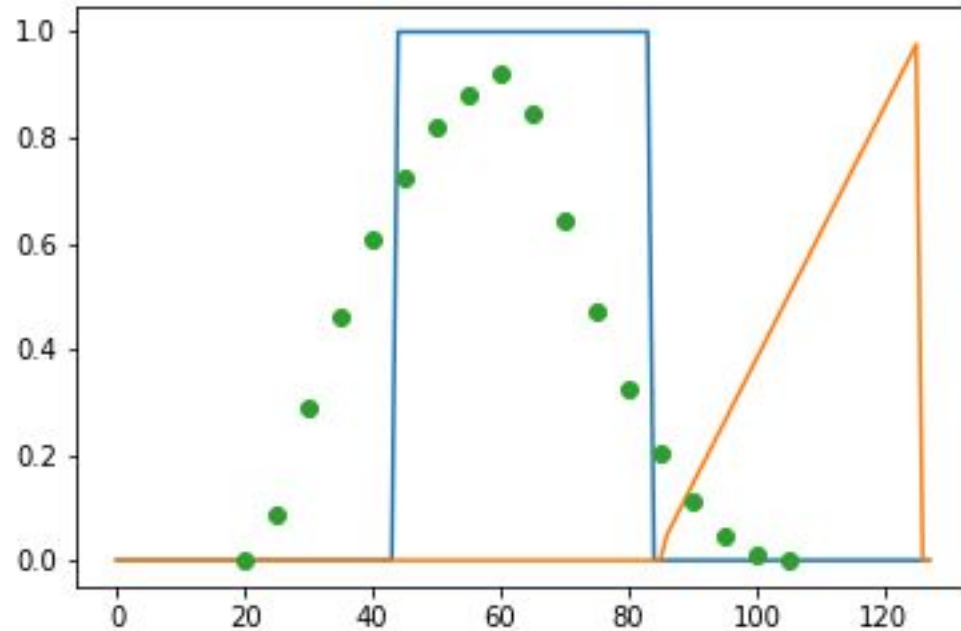
# Cross correlation function in 1D



# Cross correlation function in 1D



# Cross correlation function in 1D

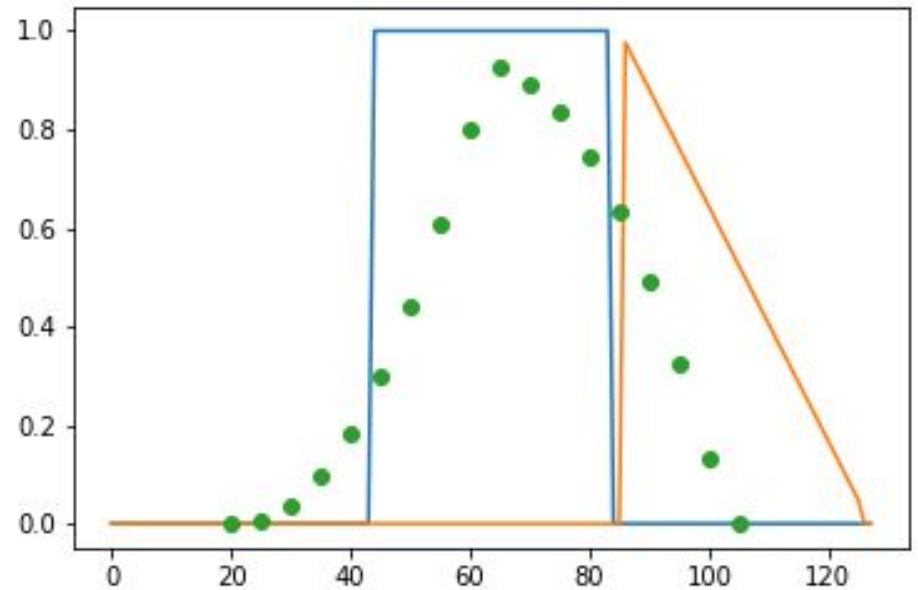
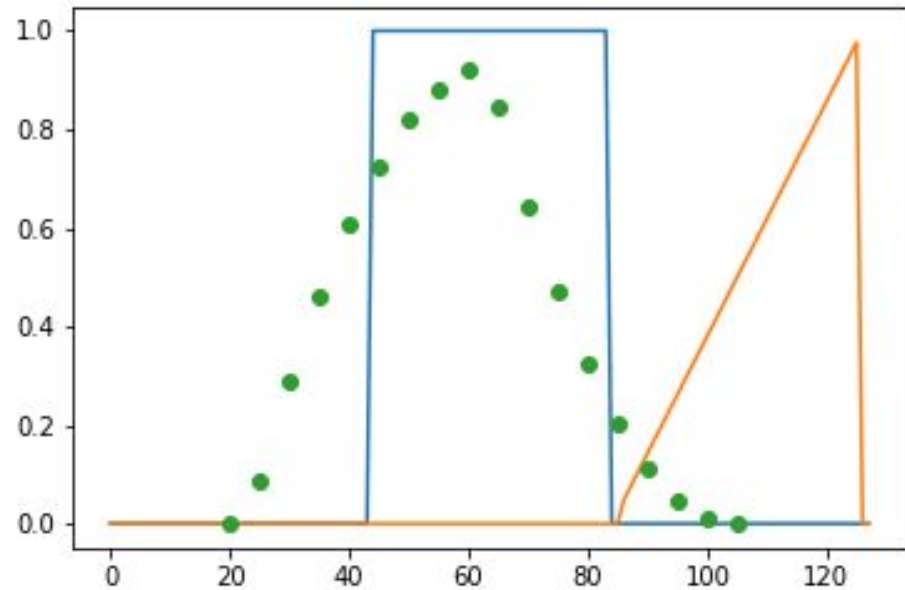
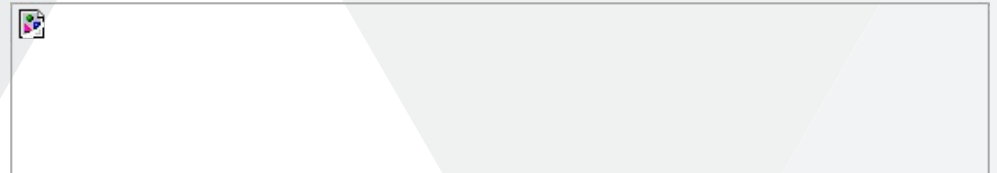


# Cross correlation function in 1D

Cross-correlation



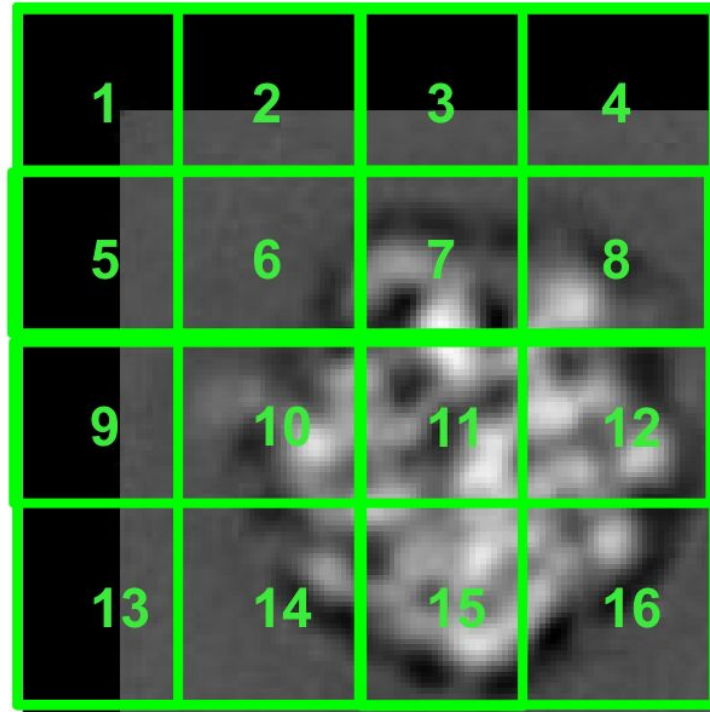
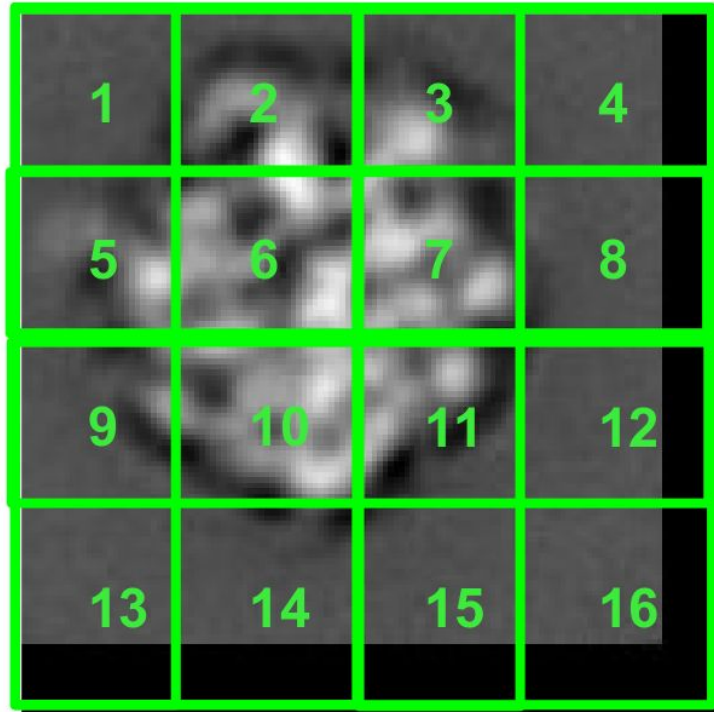
Convolution



# Cross correlation function in 2D



# Image alignment in 2D





# Image alignment in 2D

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

Image  $f$

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

Image  $g$

$$\begin{aligned} \text{Unnormalized CCC} = & f_1g_1 + f_2g_2 + f_3g_3 + f_4g_4 + f_5g_5 + f_6g_6 + f_7g_7 + f_8g_8 \\ & + f_9g_9 + f_{10}g_{10} + f_{11}g_{11} + f_{12}g_{12} + f_{13}g_{13} + f_{14}g_{14} + f_{15}g_{15} + f_{16}g_{16} \end{aligned}$$

# Image alignment in 2D

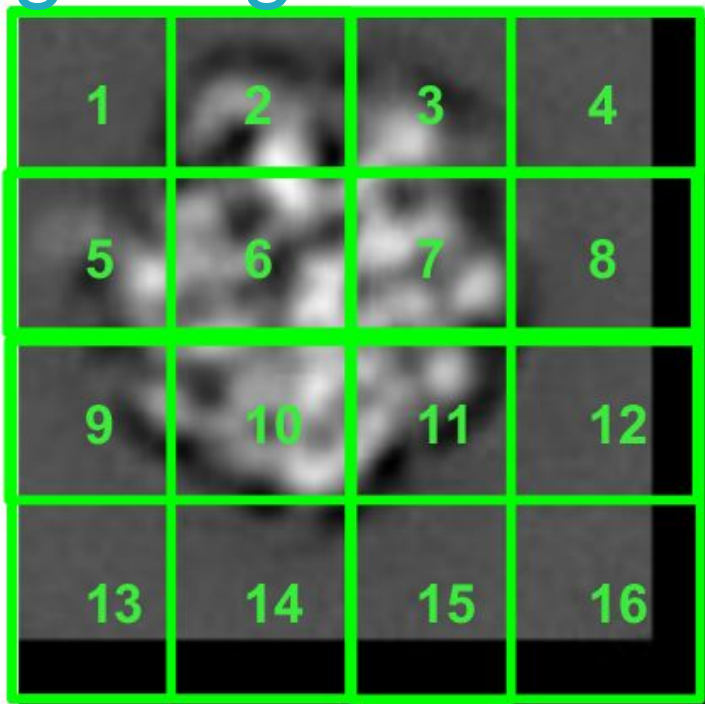


Image  $f$

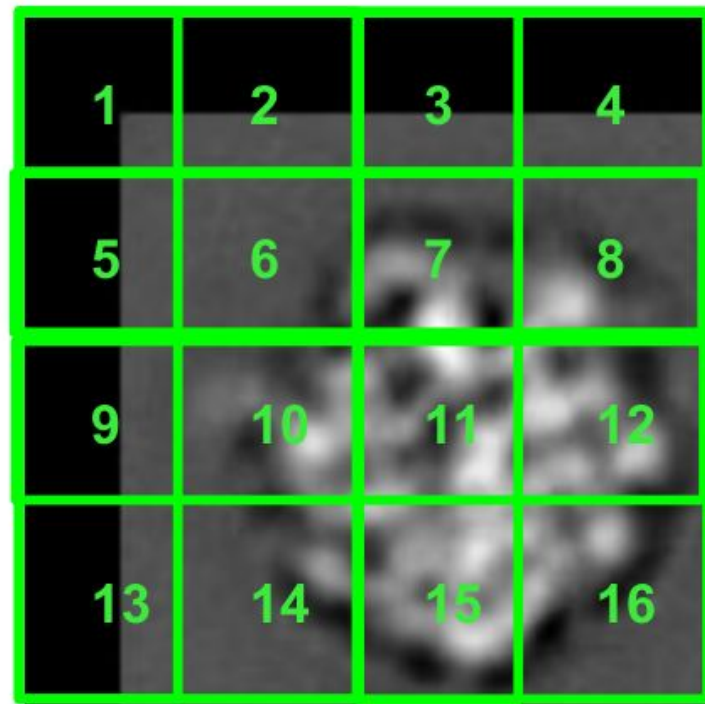
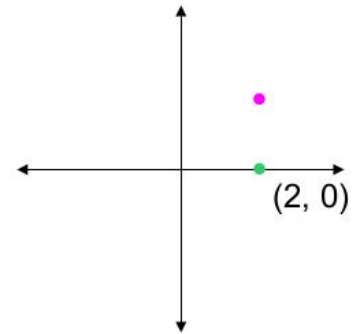
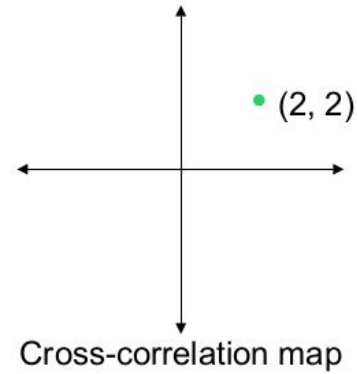
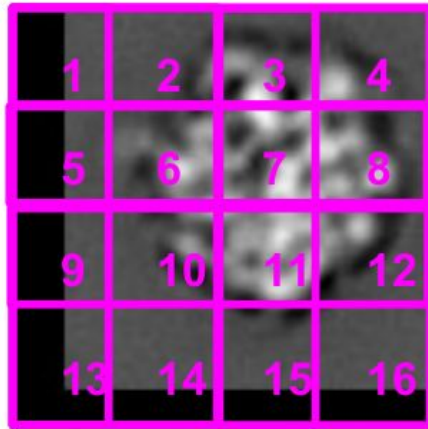
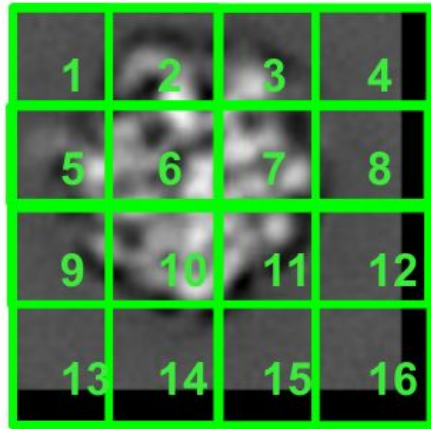
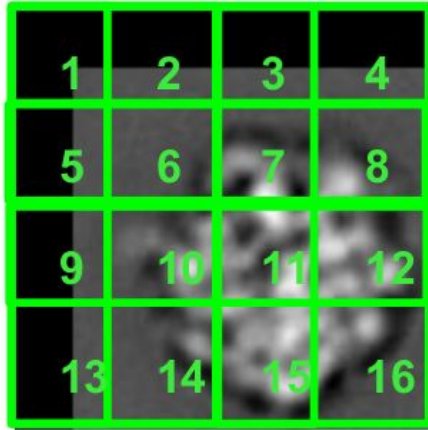
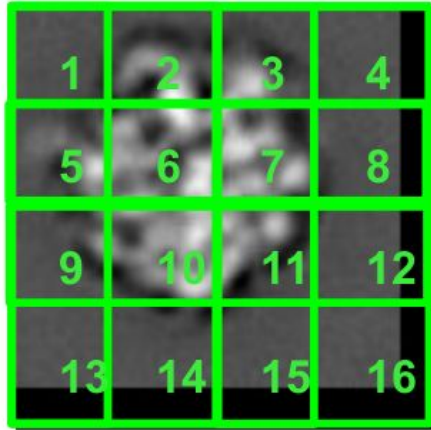


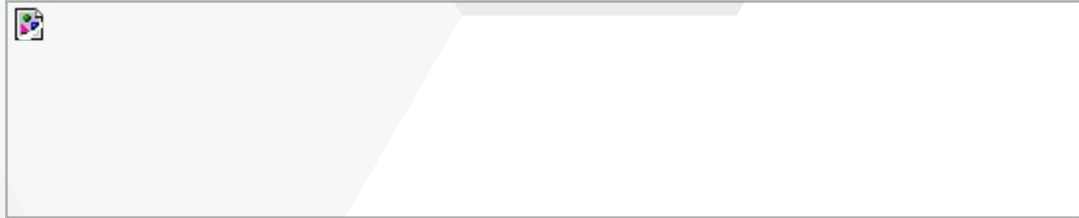
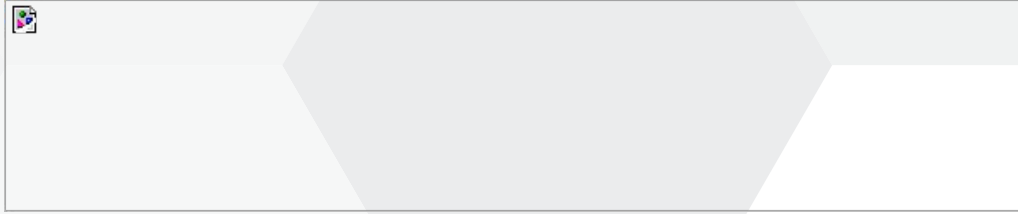
Image  $g$

$$\begin{aligned} \text{Unnormalized CCC} = & f_1g_1 + f_2g_2 + f_3g_3 + f_4g_4 + f_5g_5 + f_6g_6 + f_7g_7 + f_8g_8 \\ & + f_9g_9 + f_{10}g_{10} + f_{11}g_{11} + f_{12}g_{12} + f_{13}g_{13} + f_{14}g_{14} + f_{15}g_{15} + f_{16}g_{16} \end{aligned}$$

# Image alignment in 2D



# Cross-correlation in 2D



Convolution

$$\text{FT}(F \otimes I) = \text{FT}(F) \cdot \text{FT}(I)$$
$$\text{FT}(F \circledast I) = \text{FT}(F)^* \cdot \text{FT}(I)$$

Convolution theorem

# Cross-correlation in 2D

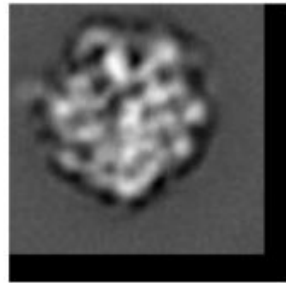


Image  $f(x)$

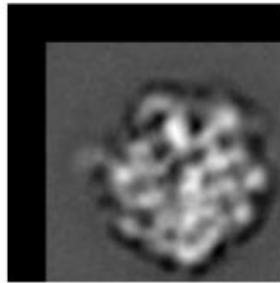
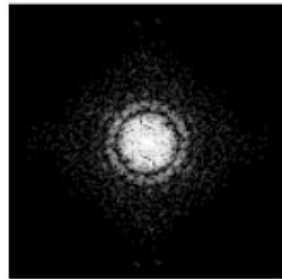
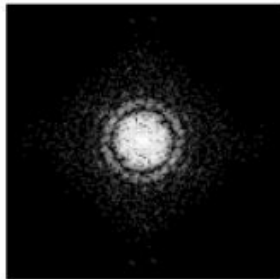


Image  $g(x)$



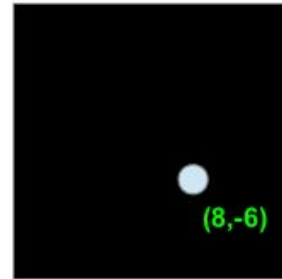
F.T.  $F^*(X)$   
(complex conjugate)

x



F.T.  $G(X)$

=

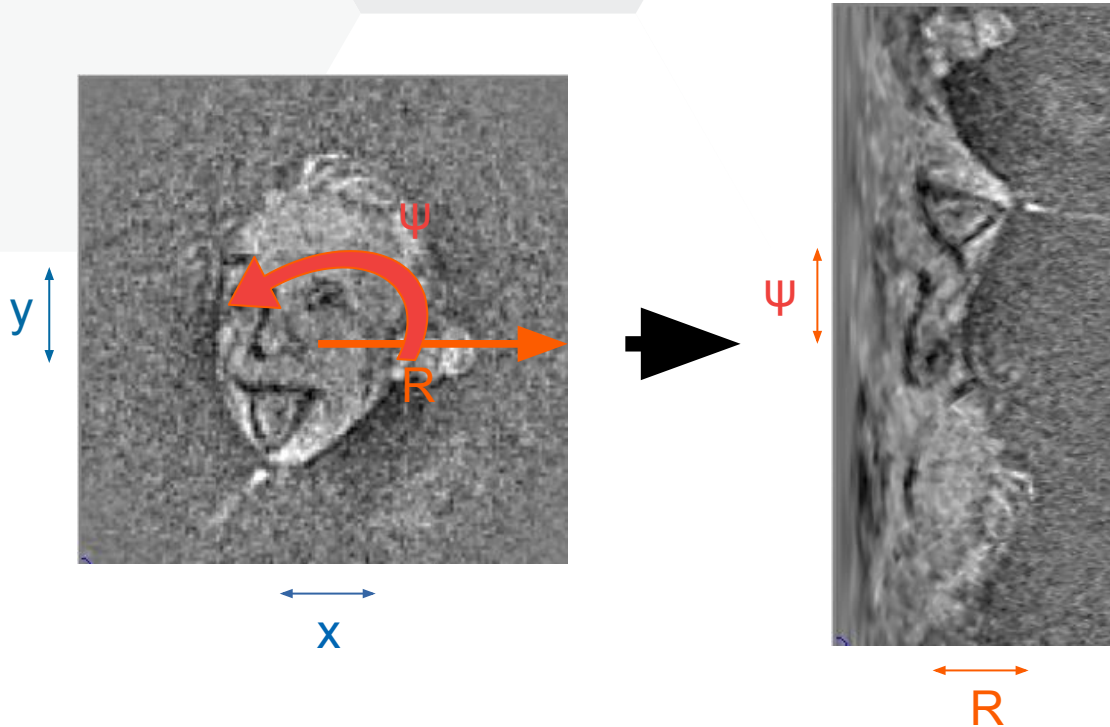


F.T. (CCF)

# Image alignment in 2D

## Image rotation

- the images contain not only shift but also rotation
- cross-correlation - image sliding over the template (shift)
- (log)-polar transform  $\rightarrow$  image transformation from cartesian to polar coordinates  $\rightarrow$  rotational problem shifted to translational problem  $\rightarrow$  utilization of similar approaches as for image shift determination



# Image alignment in 2D

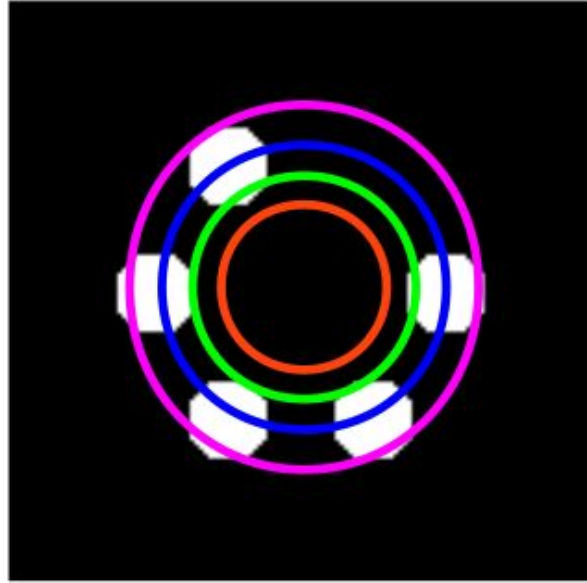


Image 1

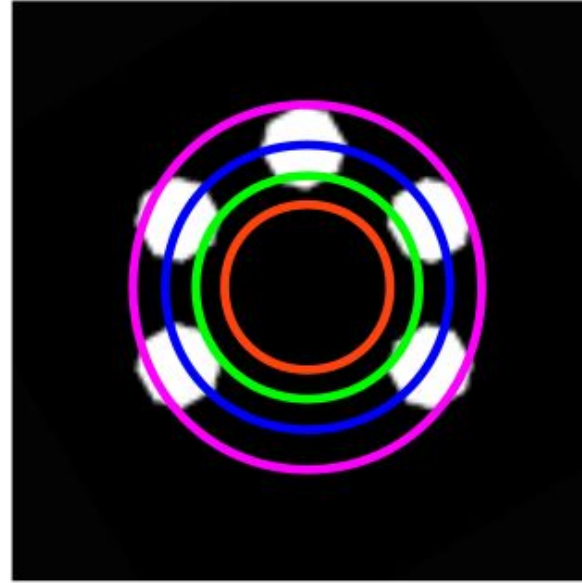


Image 2

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.



# Image alignment in 2D

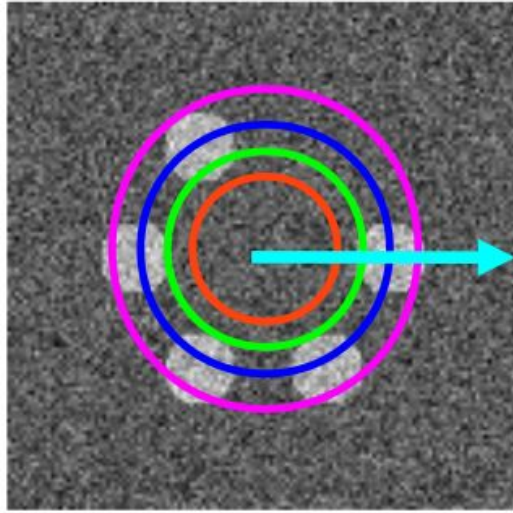


Image 1

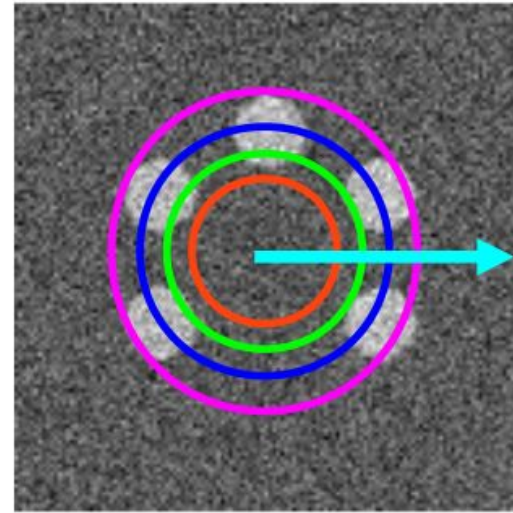
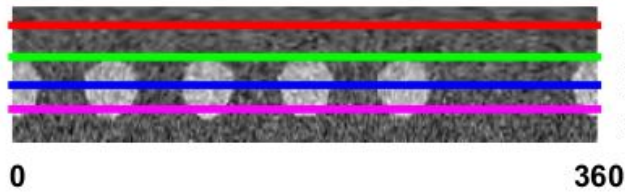
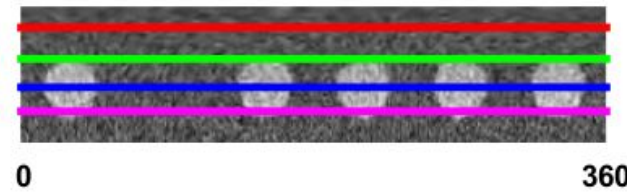


Image 2



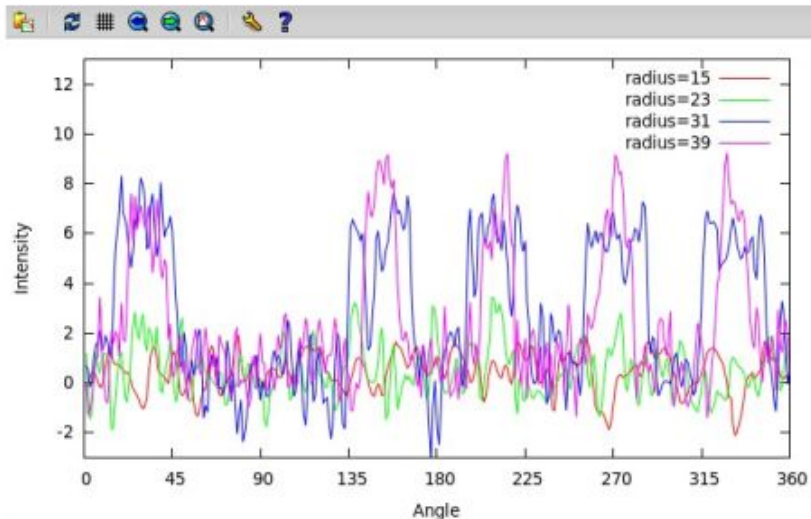
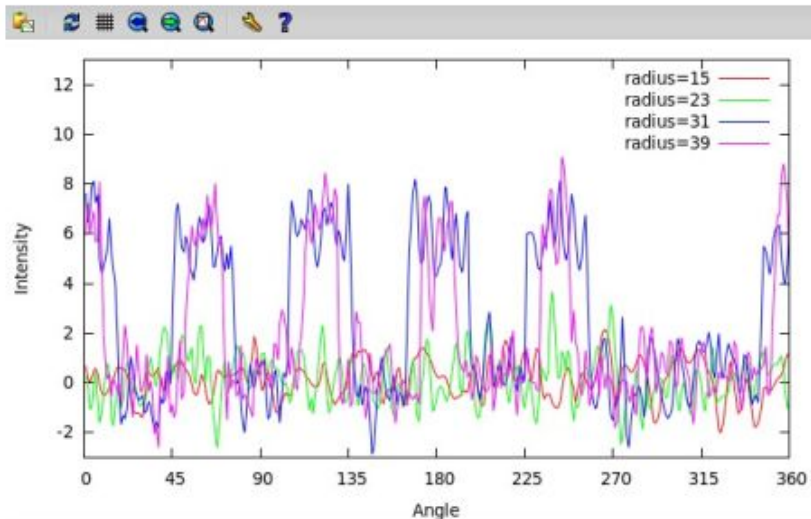
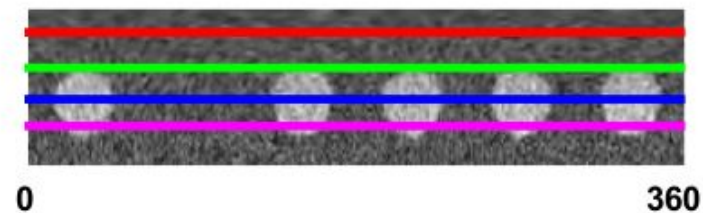
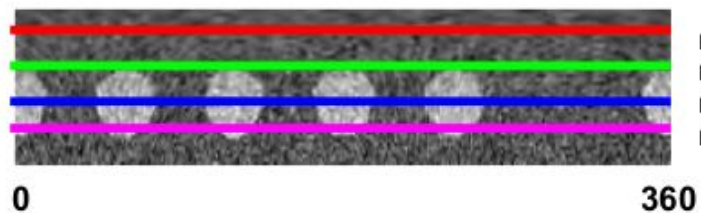
radius 1  
radius 2  
radius 3  
radius 4



Polar representation

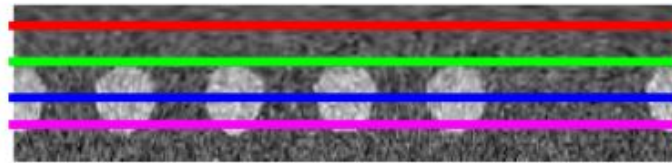


# Image alignment in 2D



# Image alignment in 2D

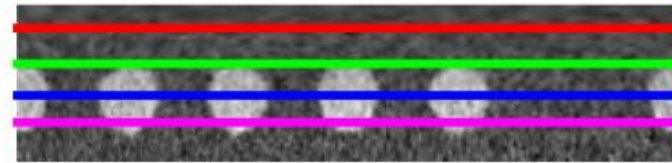
- after rotation



radius 1  
radius 2  
radius 3  
radius 4

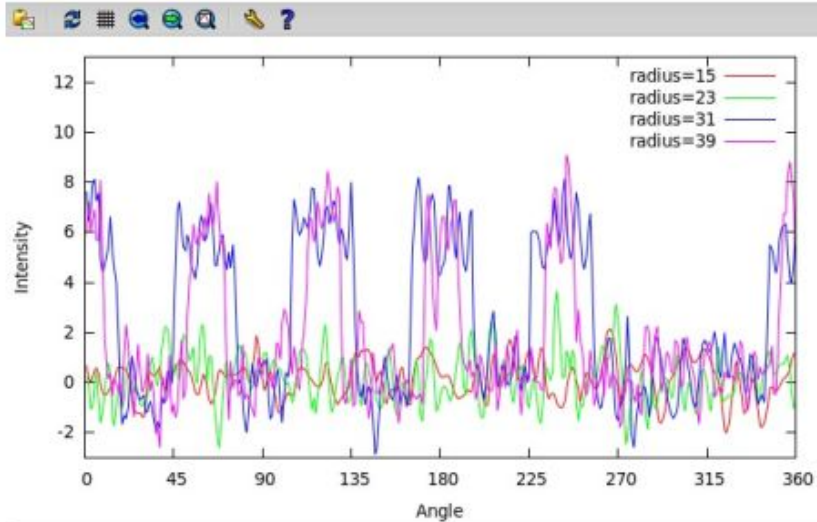
0

360

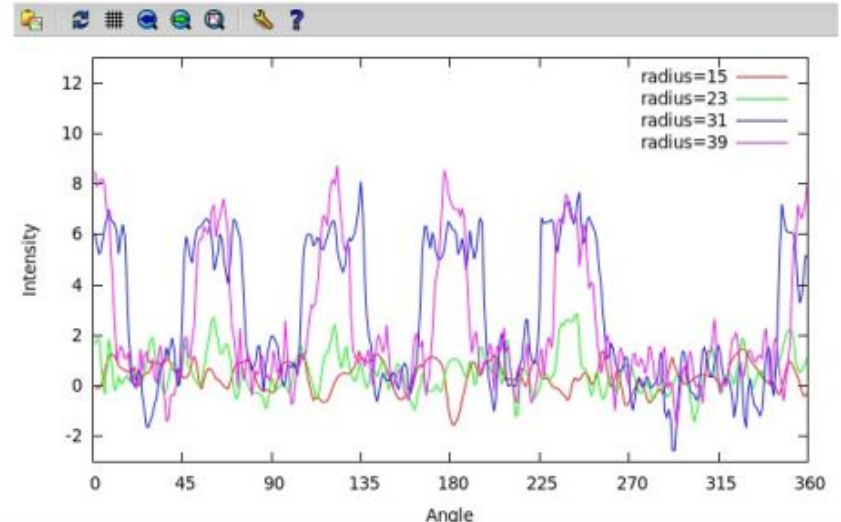


0

360



374.951, 4.53721

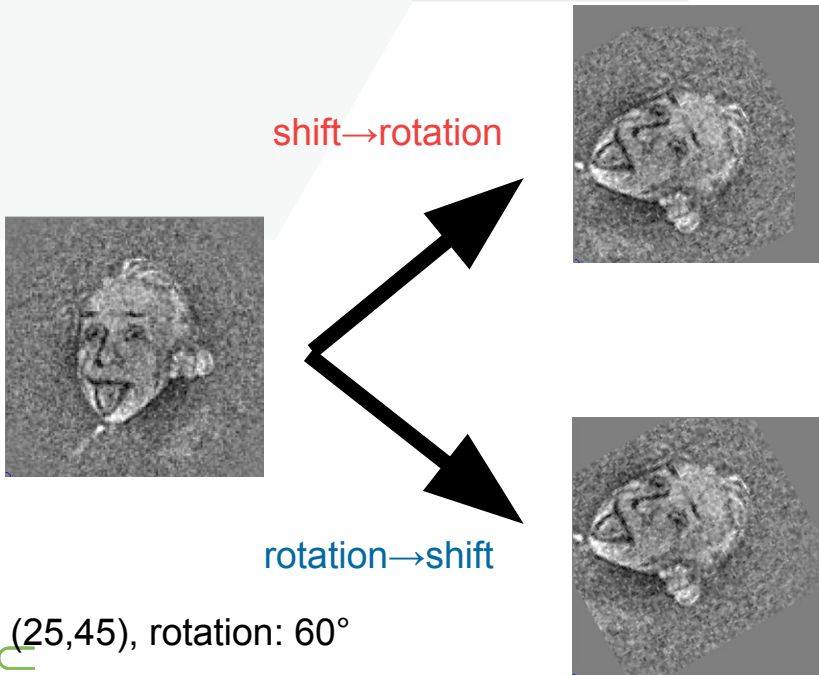


372.357, -3.21418



# Image alignment in 2D

- rotation and translation are interdependent –  $(\text{rot} \rightarrow \text{trans}) \neq (\text{trans} \rightarrow \text{rot})$   
=> **order of the operation matters**

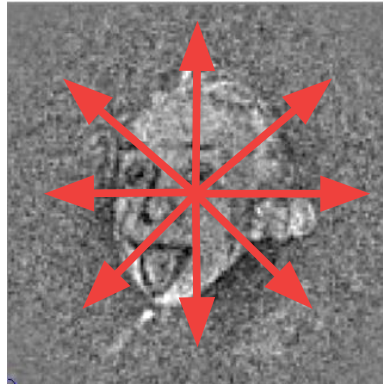


# Image alignment in 2D

- rotation and translation are interdependent – (rot→trans)  $\neq$  (trans→rot)
- define reasonable range of shifts (e.g. (-2;+2)) and perform rotational alignment for each shifted image

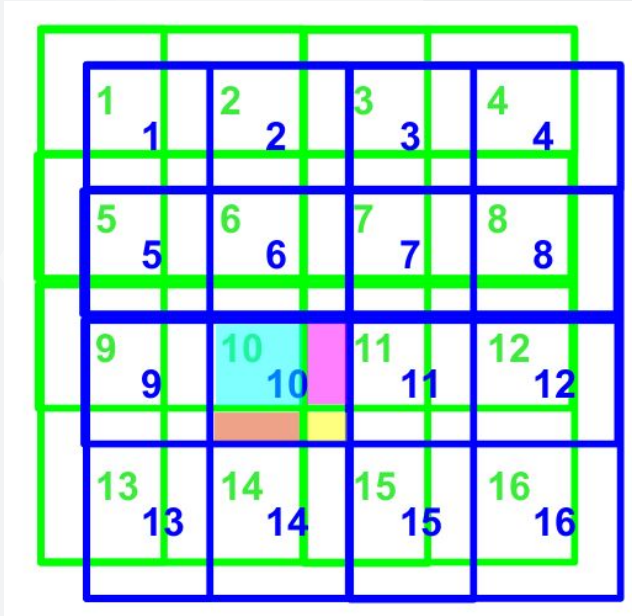
Example: for the shift of +/-2 pixels in  $x$  and  $y$  → 25 alignment rotational alignments → each alignment results in optimal rotational alignment and  $ccc$  → compare  $ccc$  and select maximal  $ccc$  to determine the final shift and translation

=> **increased complexity**



# Image alignment in 2D

## Interpolation



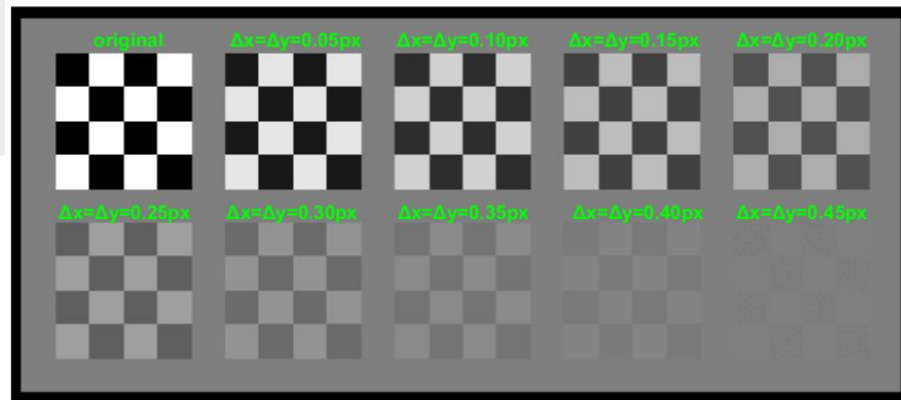
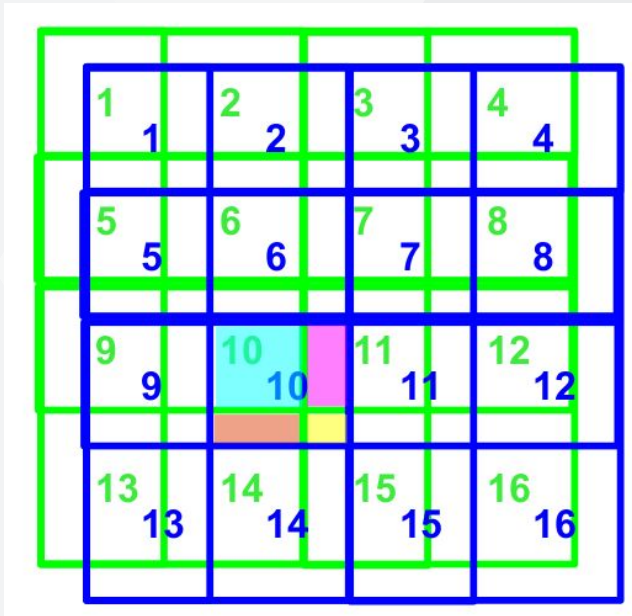
Suppose we shift the image in x & y.

The new pixels will be weighted averages of the old pixels.

The more the mix the pixels, the worse the result will be.

# Image alignment in 2D

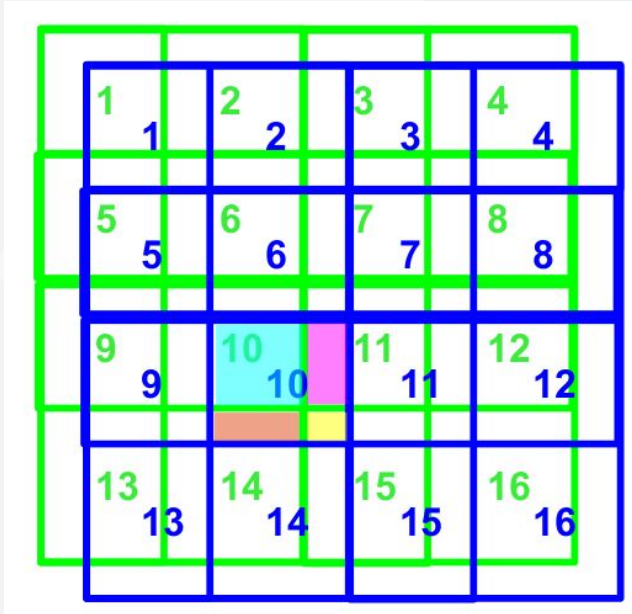
## Interpolation



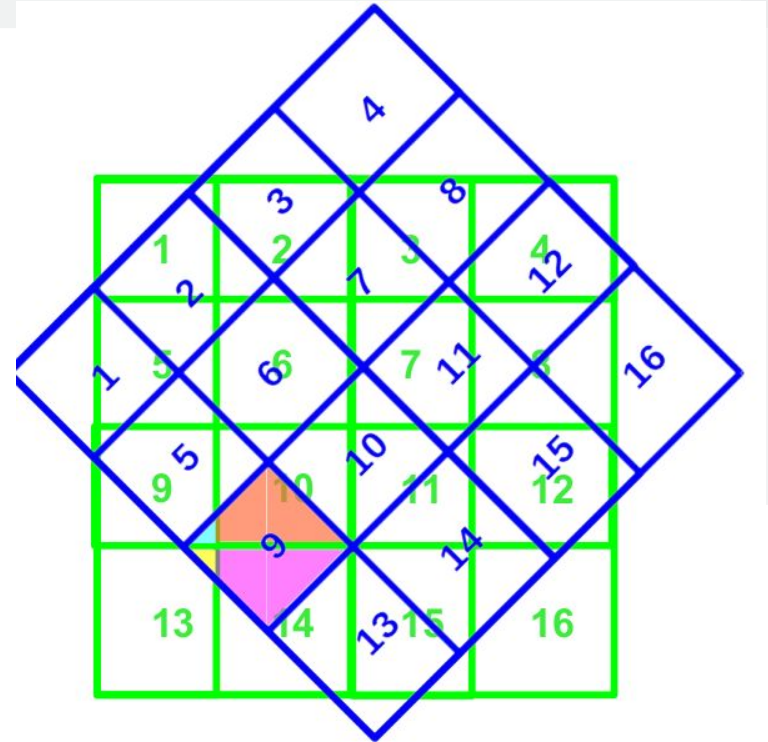
Suppose we shift the image in x & y.  
The new pixels will be weighted averages of the old pixels.  
The more the mix the pixels, the worse the result will be.

# Image alignment in 2D

Shift



Rotation



Suppose we shift the image in x & y.  
The new pixels will be weighted averages of the old pixels.  
The more the mix the pixels, the worse the result will be.



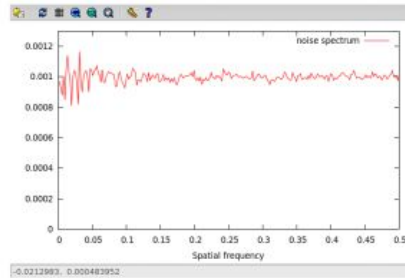
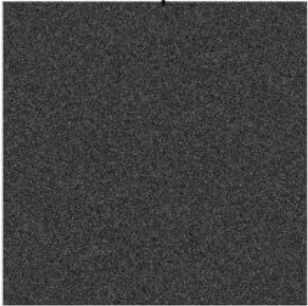
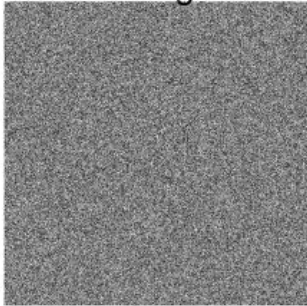
# Image alignment in 2D

Interpolation  
Image

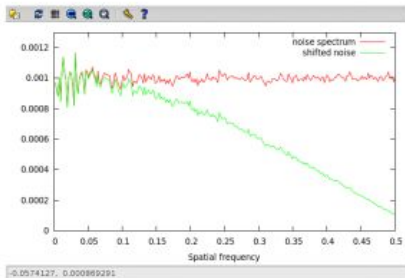
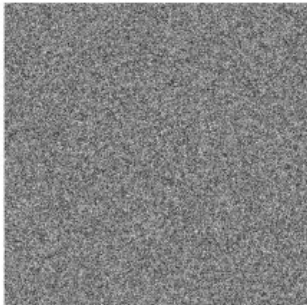
Power spectrum

Power spectrum profile

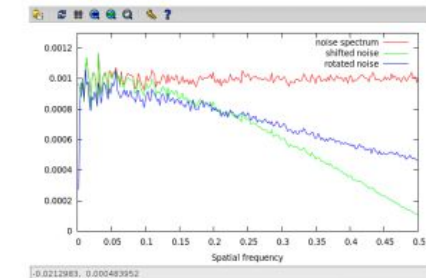
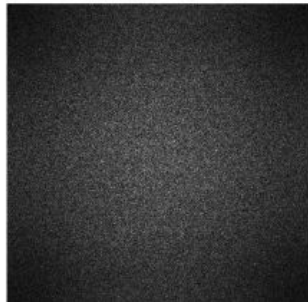
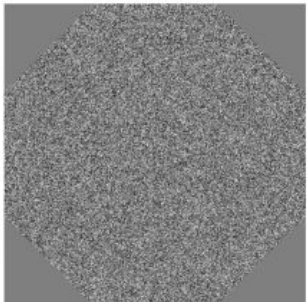
Original



Shifted by (0.5,0.5) px



Rotated by 45°



The Fourier transform of noise is noise

- “White” noise is evenly distributed in Fourier space
- “White” means that each pixel is independent





# Image alignment in 2D

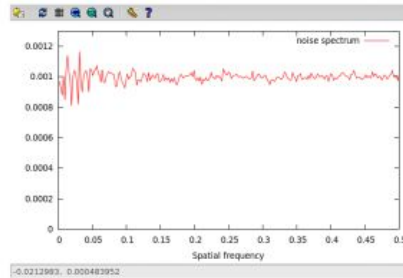
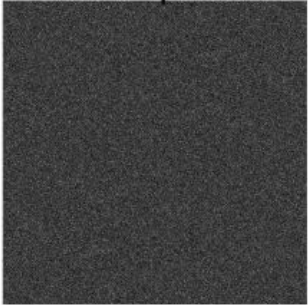
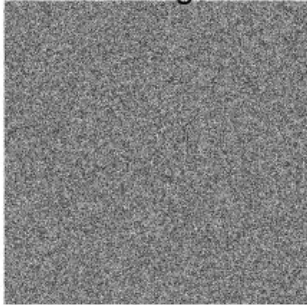
Interpolation

Image

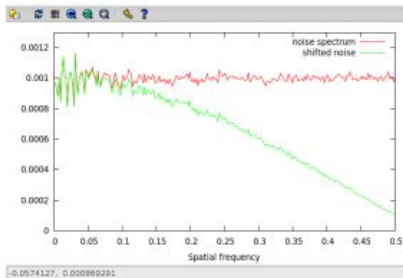
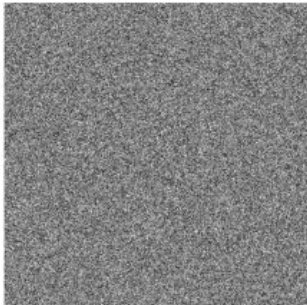
Power spectrum

Power spectrum profile

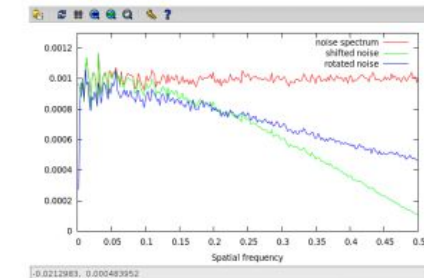
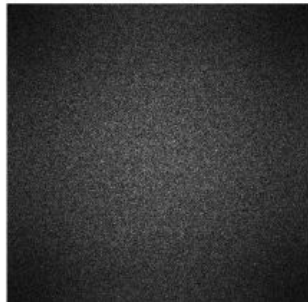
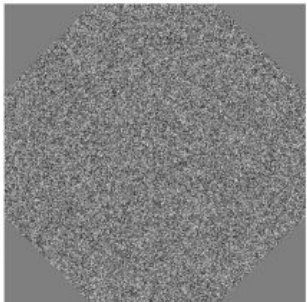
Original



Shifted by (0.5,0.5) px



Rotated by 45°



The Fourier transform of noise is noise

- “White” noise is evenly distributed in Fourier space
- “White” means that each pixel is independent

The degradation of the images means that we should minimize the number of interpolations.



# Image alignment in 3D

Two translational:

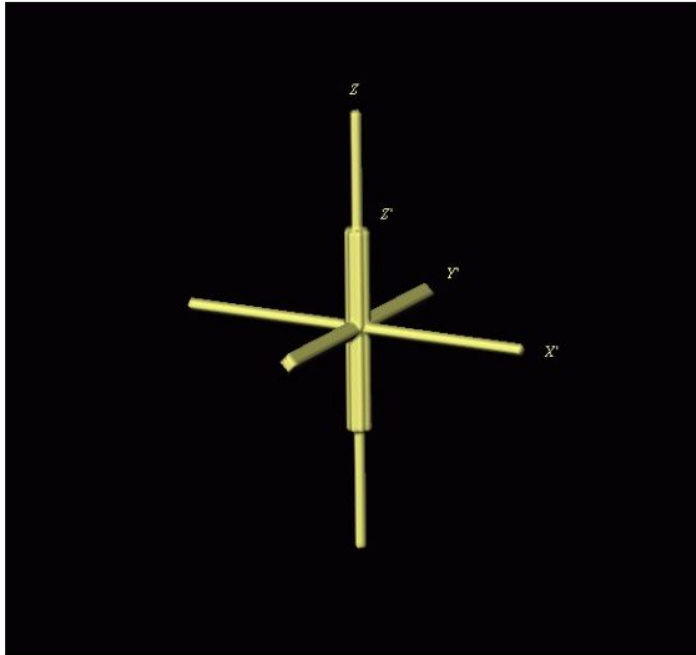
- $\Delta x$
- $\Delta y$

Three orientational  
(Euler angles):

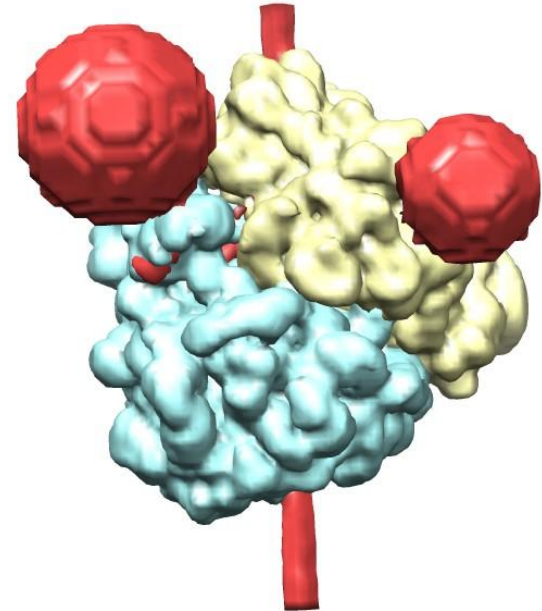
- phi (about z axis)
- theta (about y)
- psi (about new z)

These are determined in 2D.

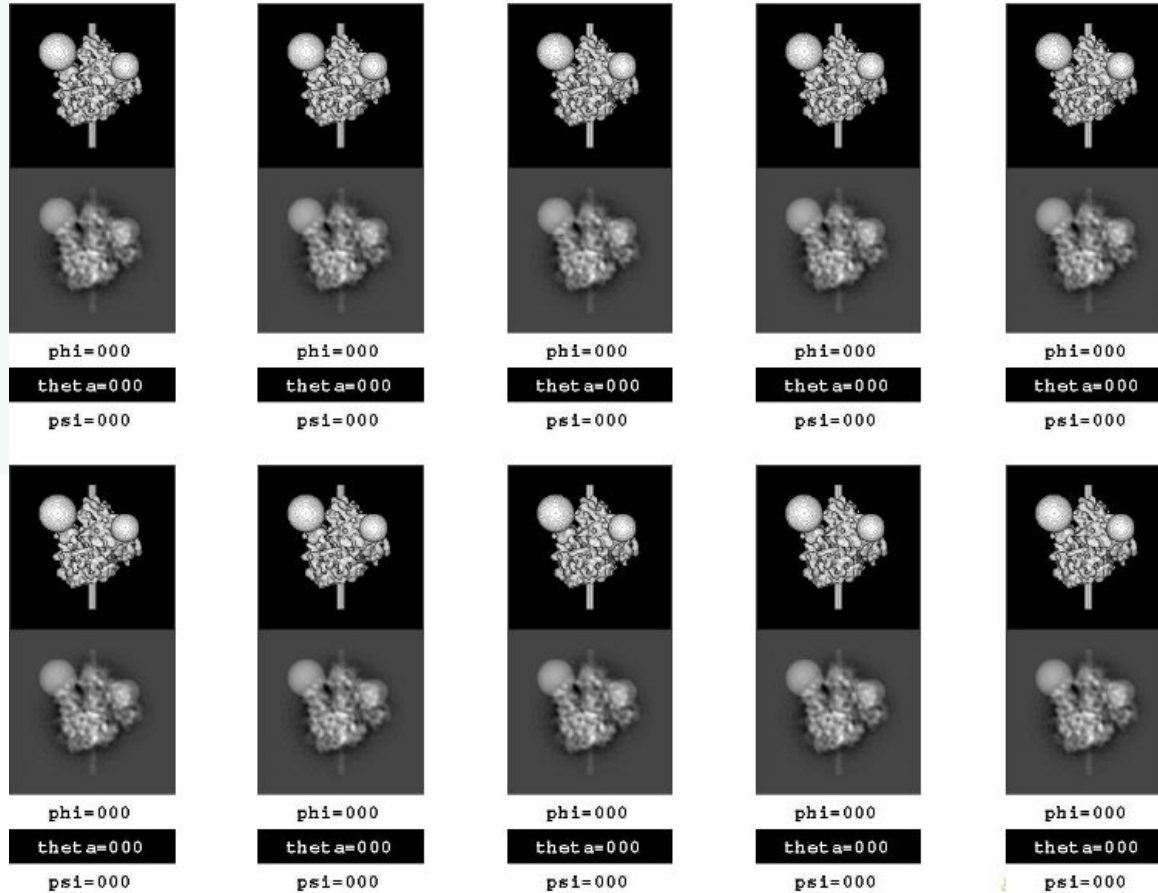
These are determined in 3D.



<http://www.wadsworth.org>



# Image alignment in 3D



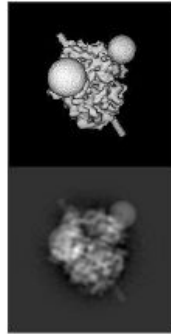
# Image alignment in 3D



phi=000

theta=000

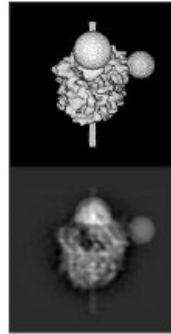
psi=000



phi=036

theta=030

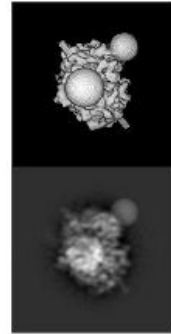
psi=000



phi=000

theta=045

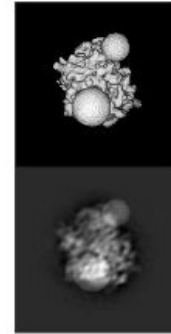
psi=000



phi=048

theta=045

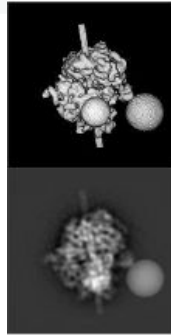
psi=000



phi=072

theta=045

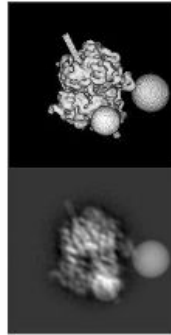
psi=000



phi=192

theta=045

psi=000



phi=216

theta=045

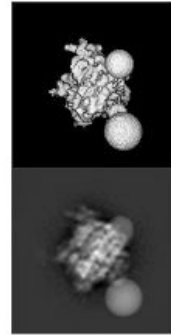
psi=000



phi=016

theta=075

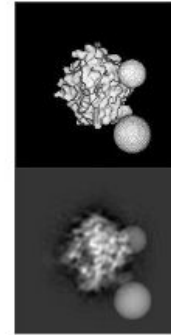
psi=000



phi=115

theta=075

psi=000



phi=131

theta=090

psi=000

# 3D reconstruction

1. Different orientations
2. Known orientations
3. Many particles
4. CTF parameters



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

Your sample isn't guaranteed to adopt different orientations, in which case you may need to explicitly tilt the microscope stage.

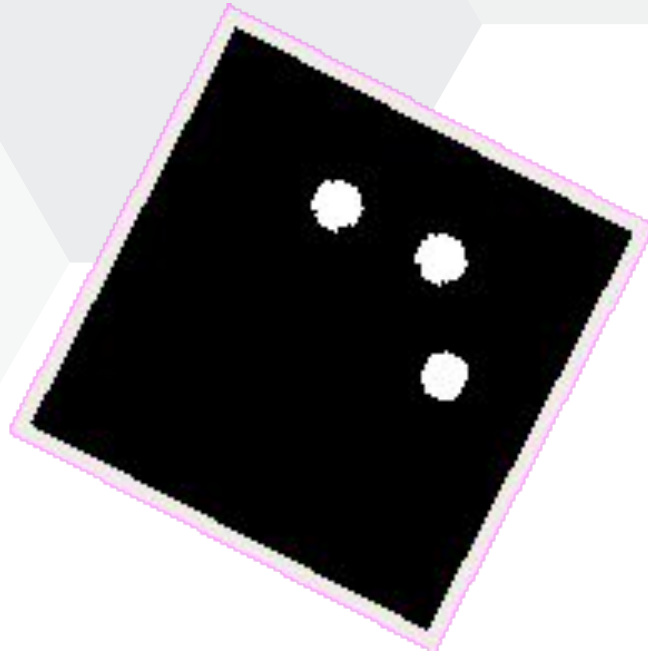
# 3D reconstruction

Two general ways for 3D reconstruction:

- Real space
- Fourier space

# 3D reconstruction

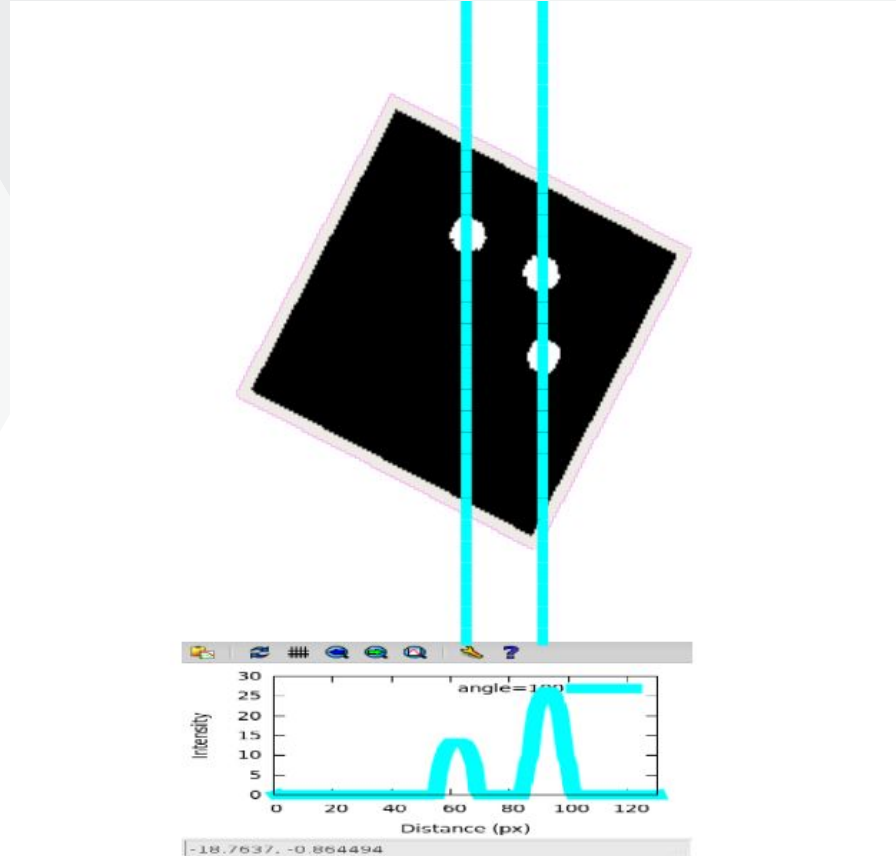
Real space reconstruction



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.

# 3D reconstruction

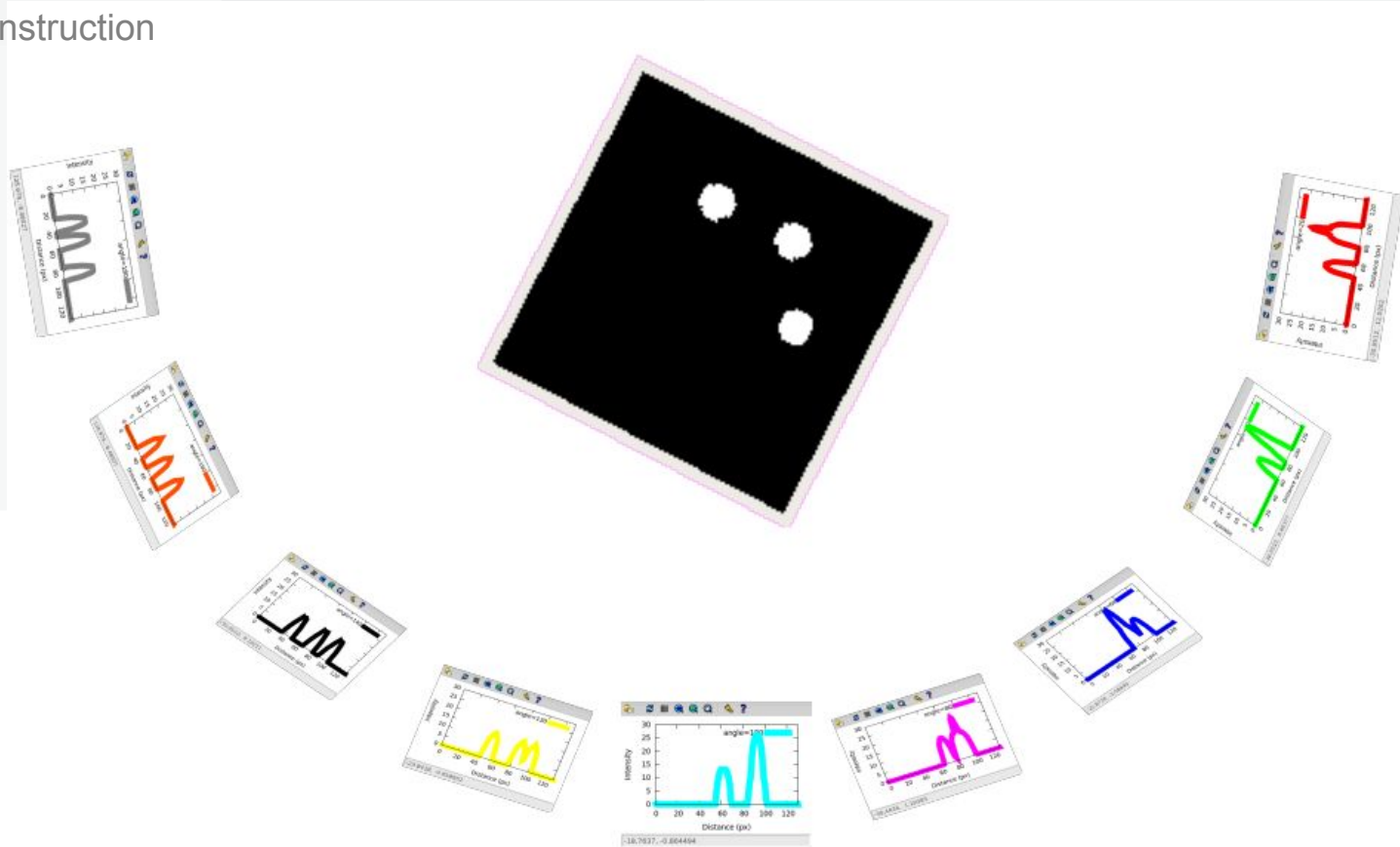
Real space reconstruction





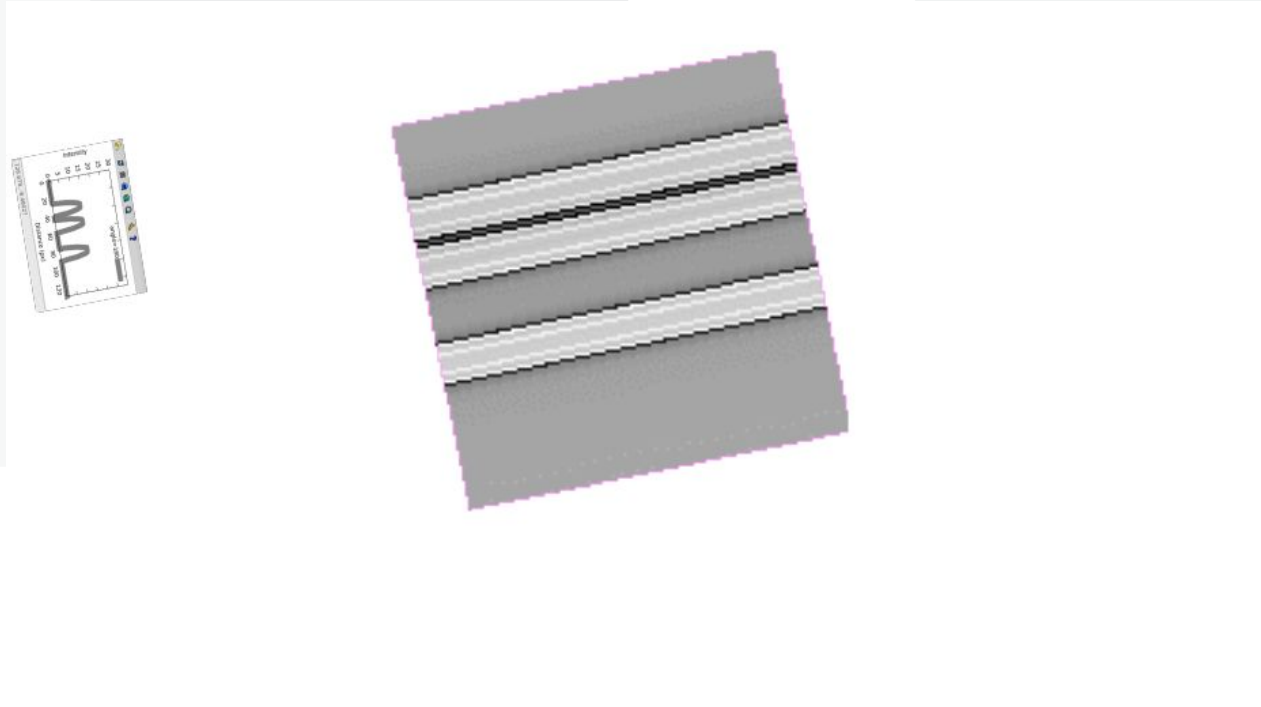
# 3D reconstruction

Real space reconstruction



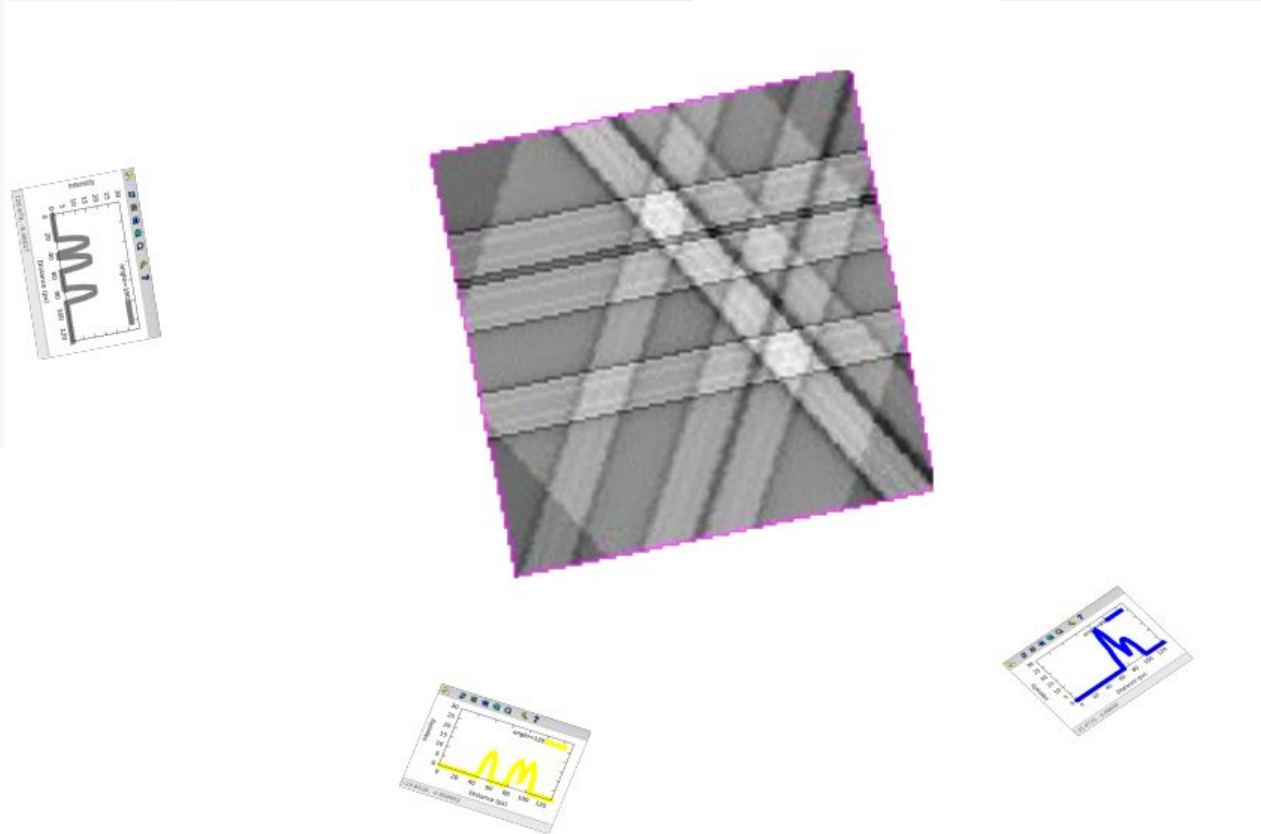
# 3D reconstruction

- reconstruction is the inversion of projection



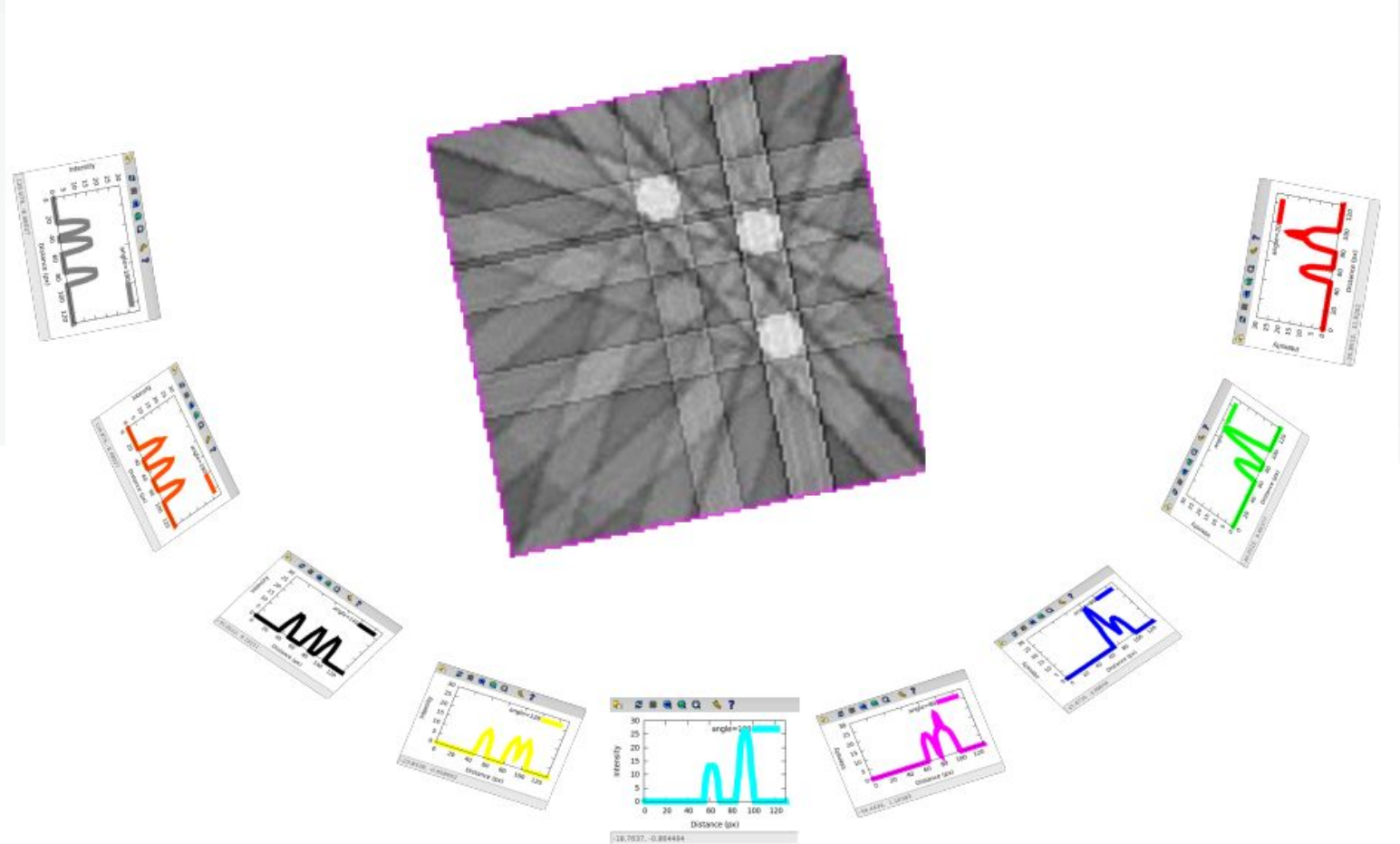
# 3D reconstruction

- reconstruction is the inversion of projection



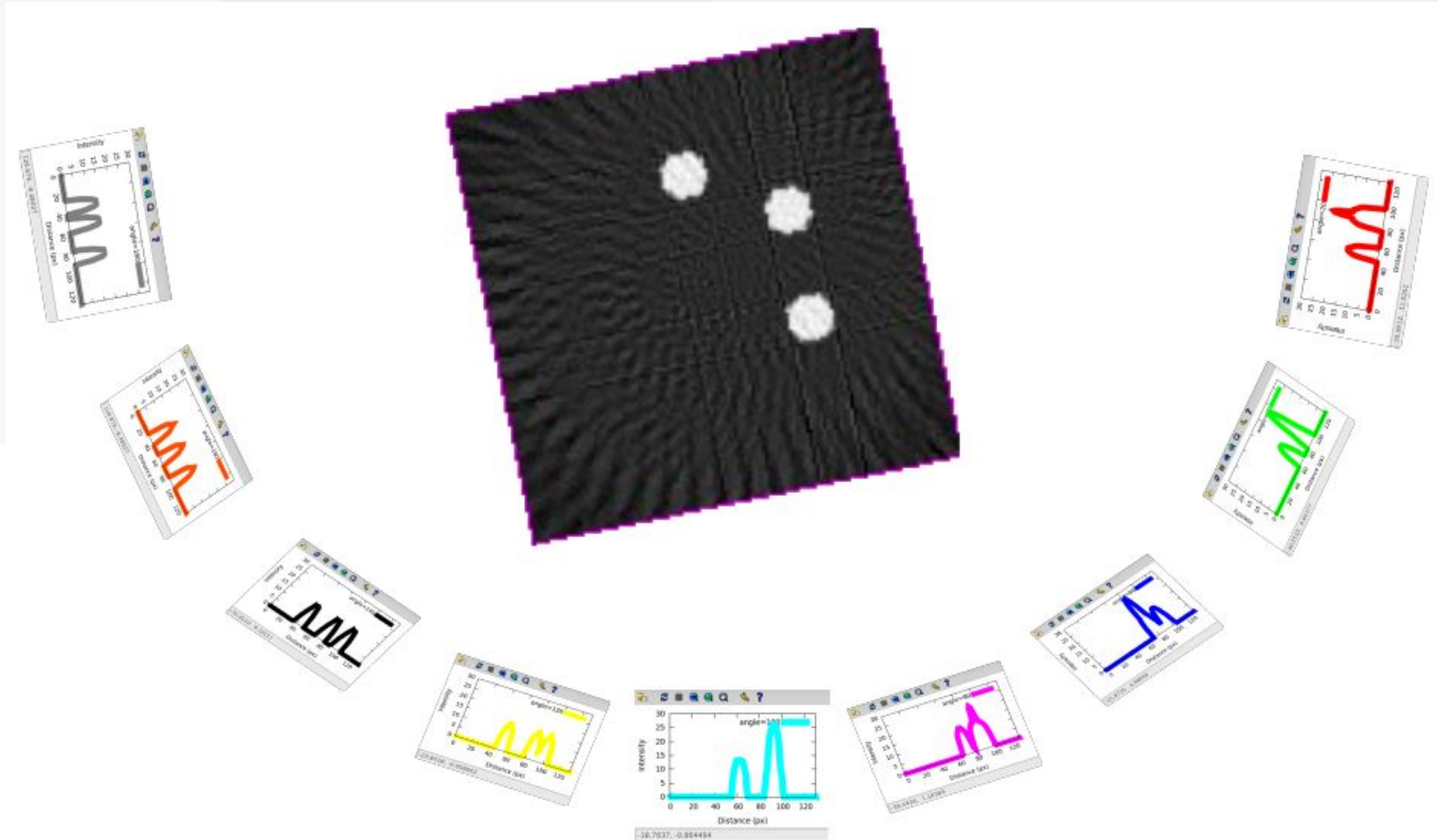
# 3D reconstruction

- reconstruction is the inversion of projection



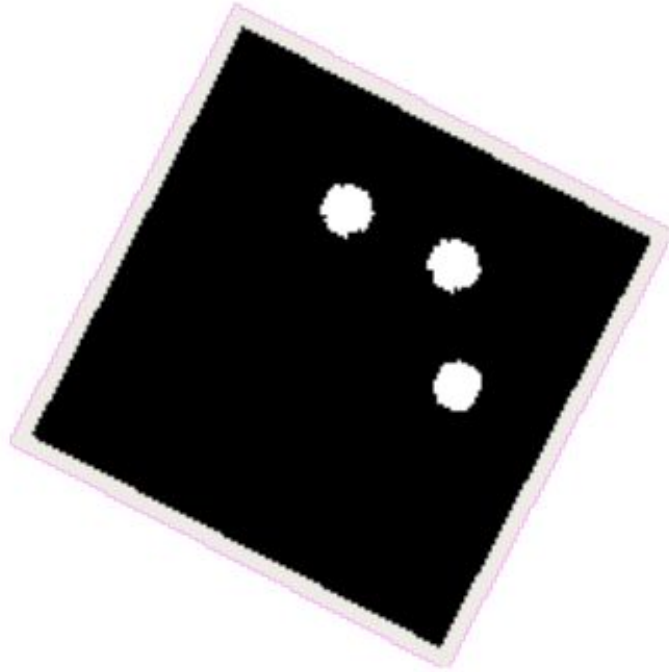
# 3D reconstruction

- reconstruction is the inversion of projection

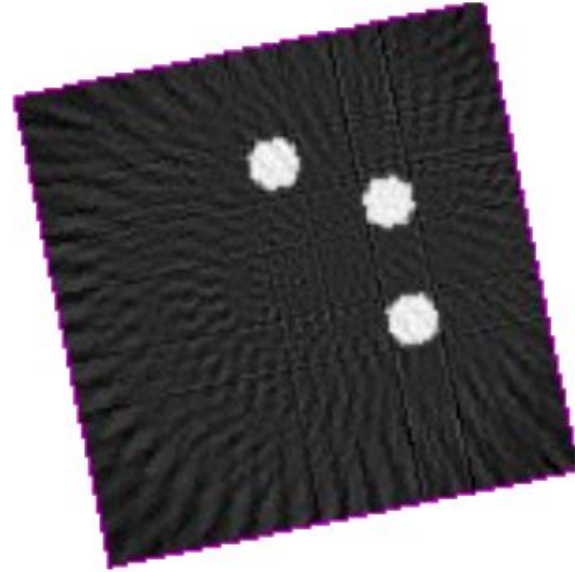


# 3D reconstruction

Original



Reconstructed



The reconstruction does not agree well with the projections

Potential solution: Simultaneous Iterative Reconstruction Technique



# 3D reconstruction

- simultaneous iterative reconstruction technique

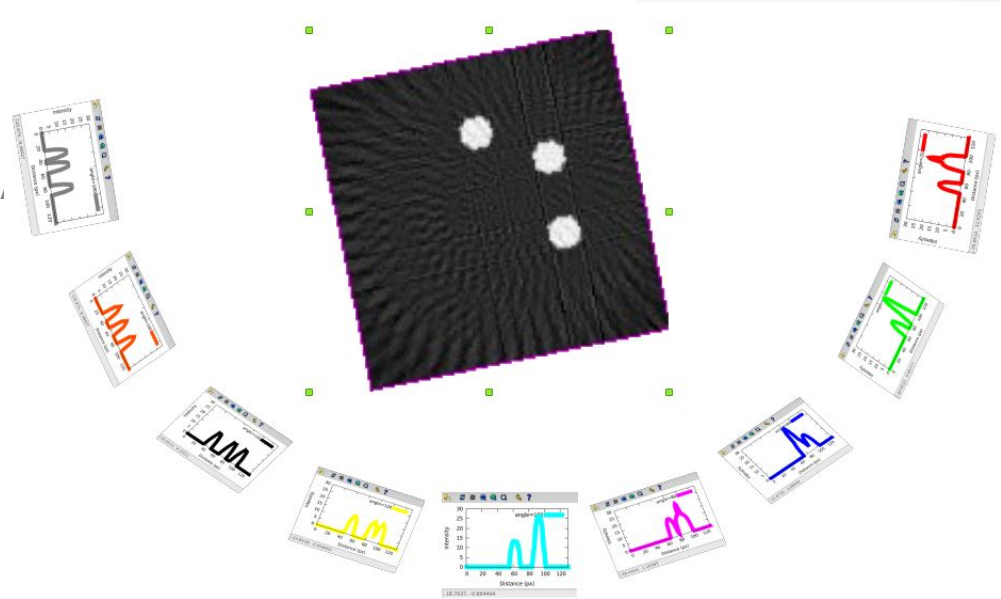
Compute re-projections of your model.

Compare the re-projections to your experimental data.  
There will be differences.

Weight the differences by a fudge factor,  $\lambda$ .

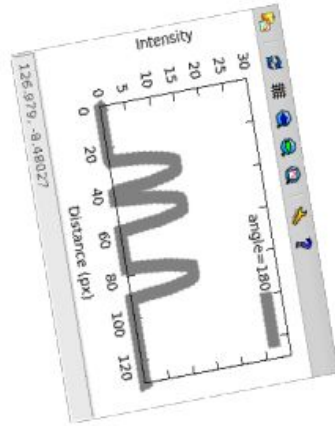
Adjust the model by the difference weighted by  $\lambda$ .

Repeat

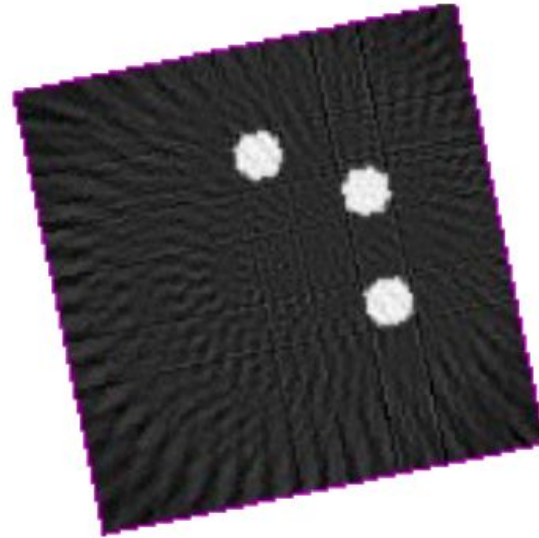


# 3D reconstruction

- simultaneous iterative reconstruction technique



Experimental projection



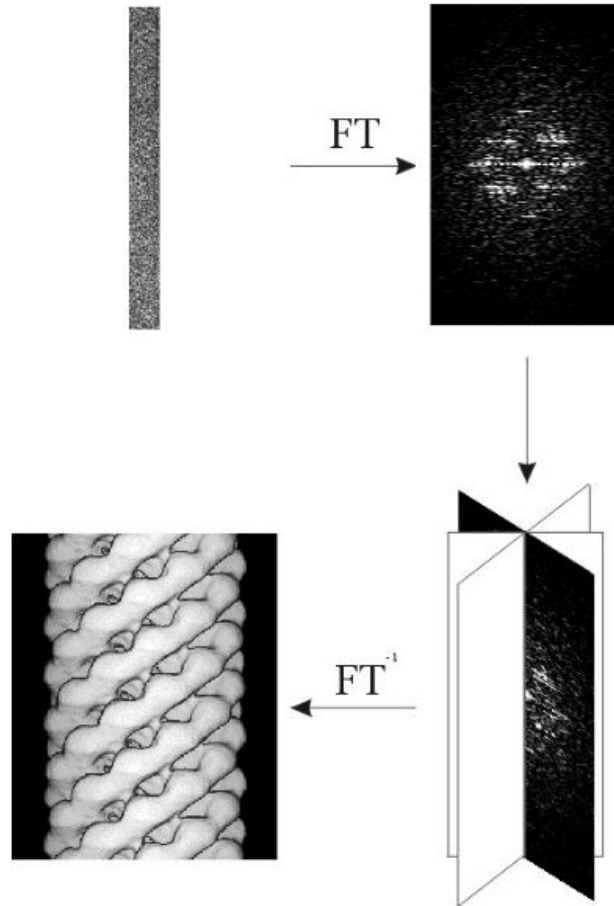
Model

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 overcompensate, and would amplify noise.

# 3D reconstruction

Fourier space reconstruction

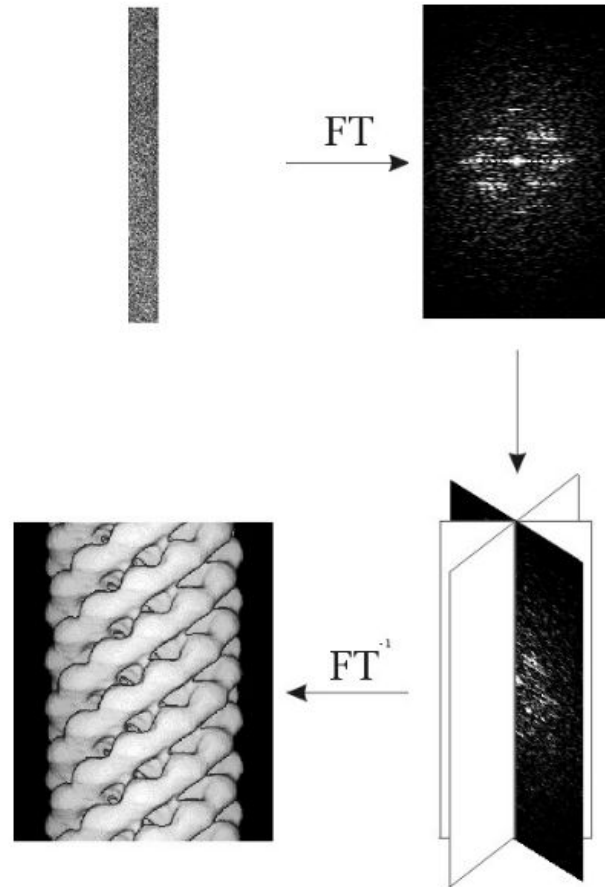


**Projection theorem**  
**Central section theorem**

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

# 3D reconstruction

Fourier space reconstruction

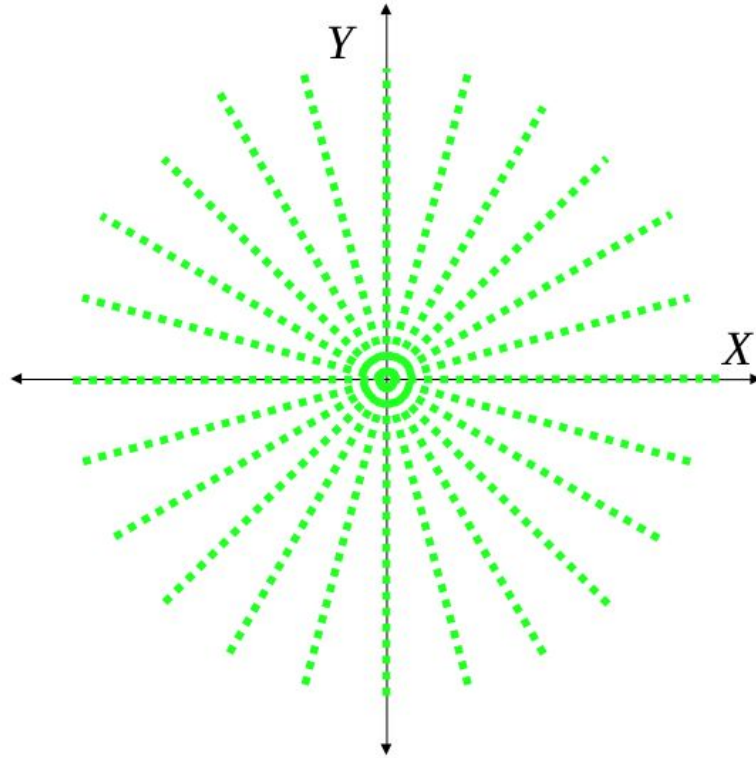


**Projection theorem**  
**Central section theorem**

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.

# 3D reconstruction

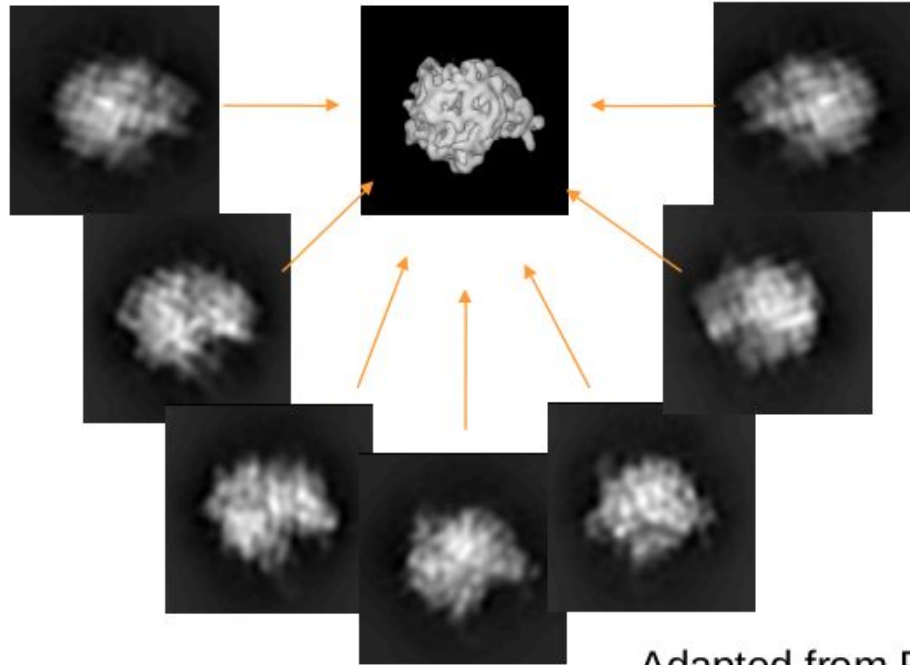
Converting from polar to Cartesian coordinates



A simple weighting scheme is to divide the weight by the radius:  
 $r^*$  weighting, or “r-weighted backprojection”

# 3D reconstruction

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



Adapted from Pawel Penczek



# 3D reconstruction

1. Different orientations
2. **Known orientations**
3. Many particles
4. CTF parameters

Two translational:

▫  $\Delta x$

▫  $\Delta y$

Three orientational  
(Euler angles):

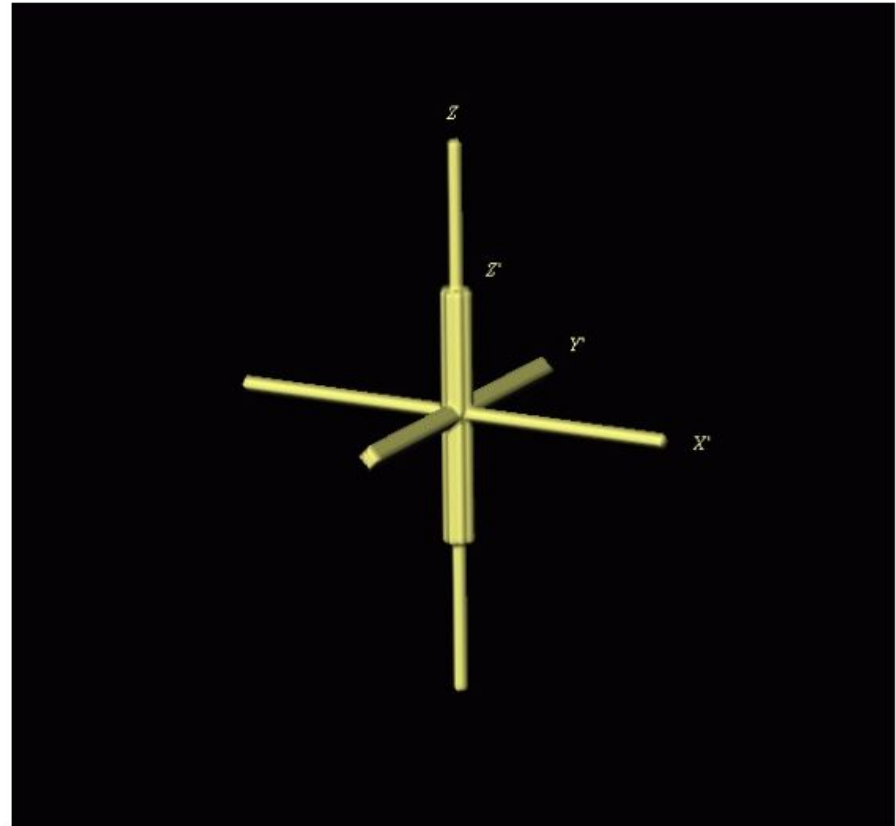
▫  $\phi$  (about z axis)

▫  $\theta$  (about y)

▫  $\psi$  (about new z)

These are determined in 2D.

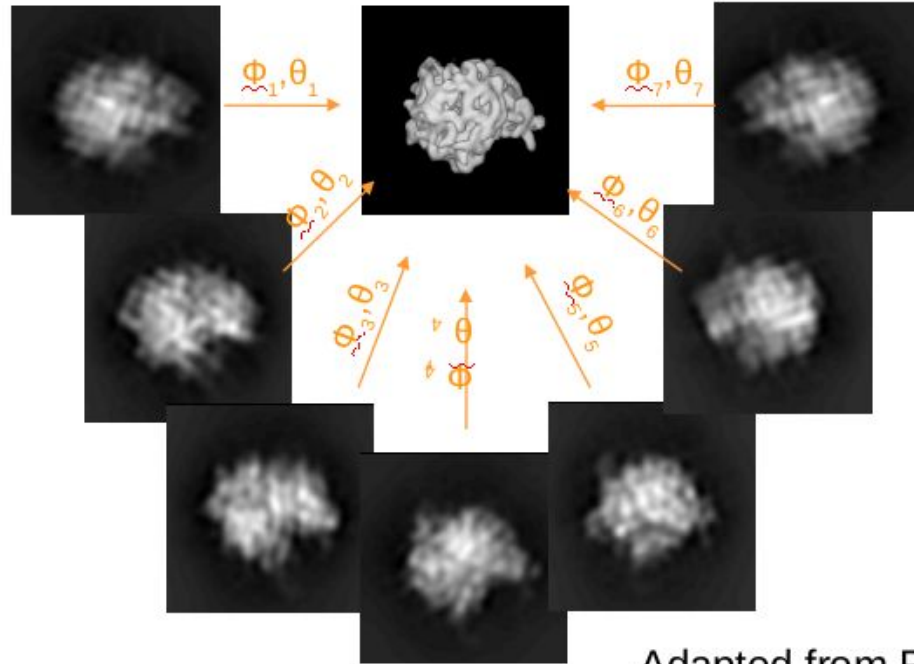
These are determined in 3D.



<http://www.wadsworth.org>

# 3D reconstruction

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

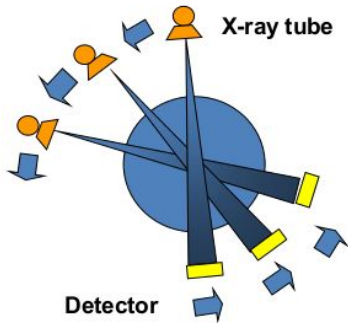
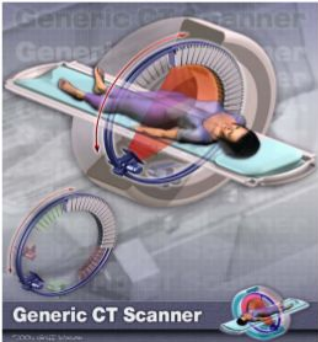


Adapted from Pawel Penczek

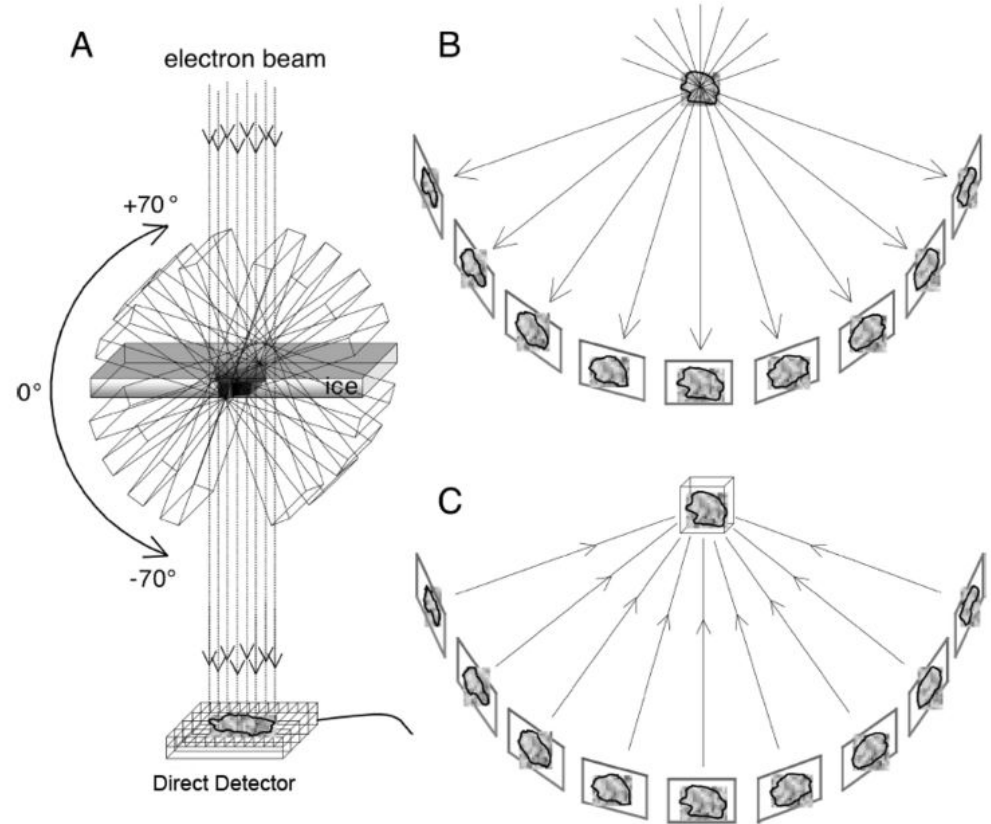
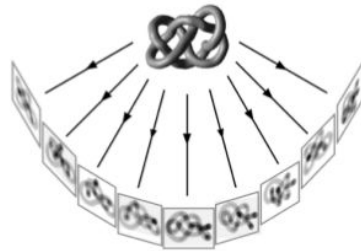
# 3D reconstruction

## Tomography

### Computer Tomography



### Electron Tomography

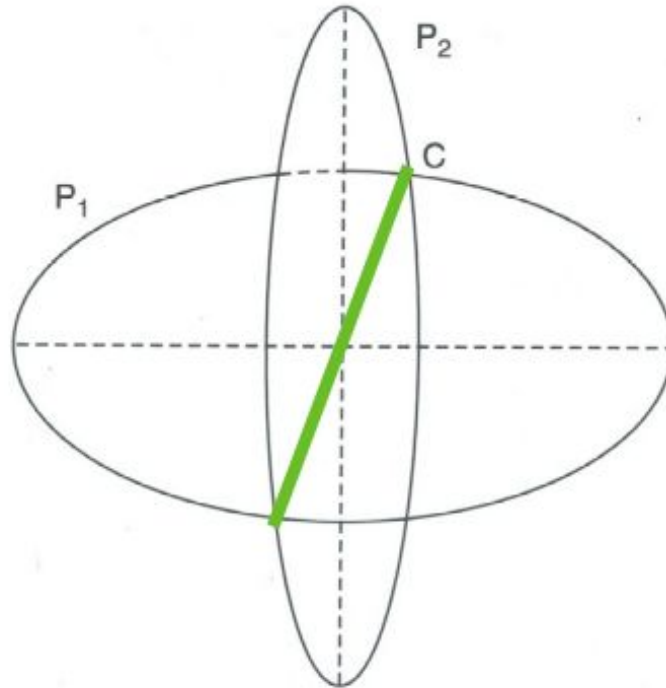


# Common lines

## Angular Reconstruction

### 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 orientations of all three.



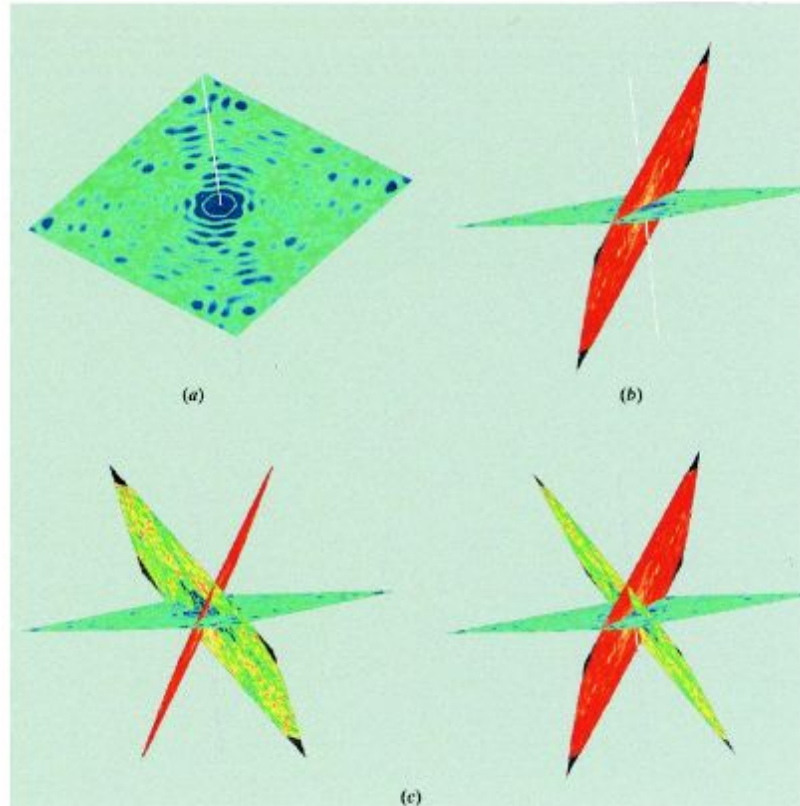
Frank, J. (2006) 3D Electron Microscopy of Macromolecular Assemblies

# Common lines

## Angular Reconstruction

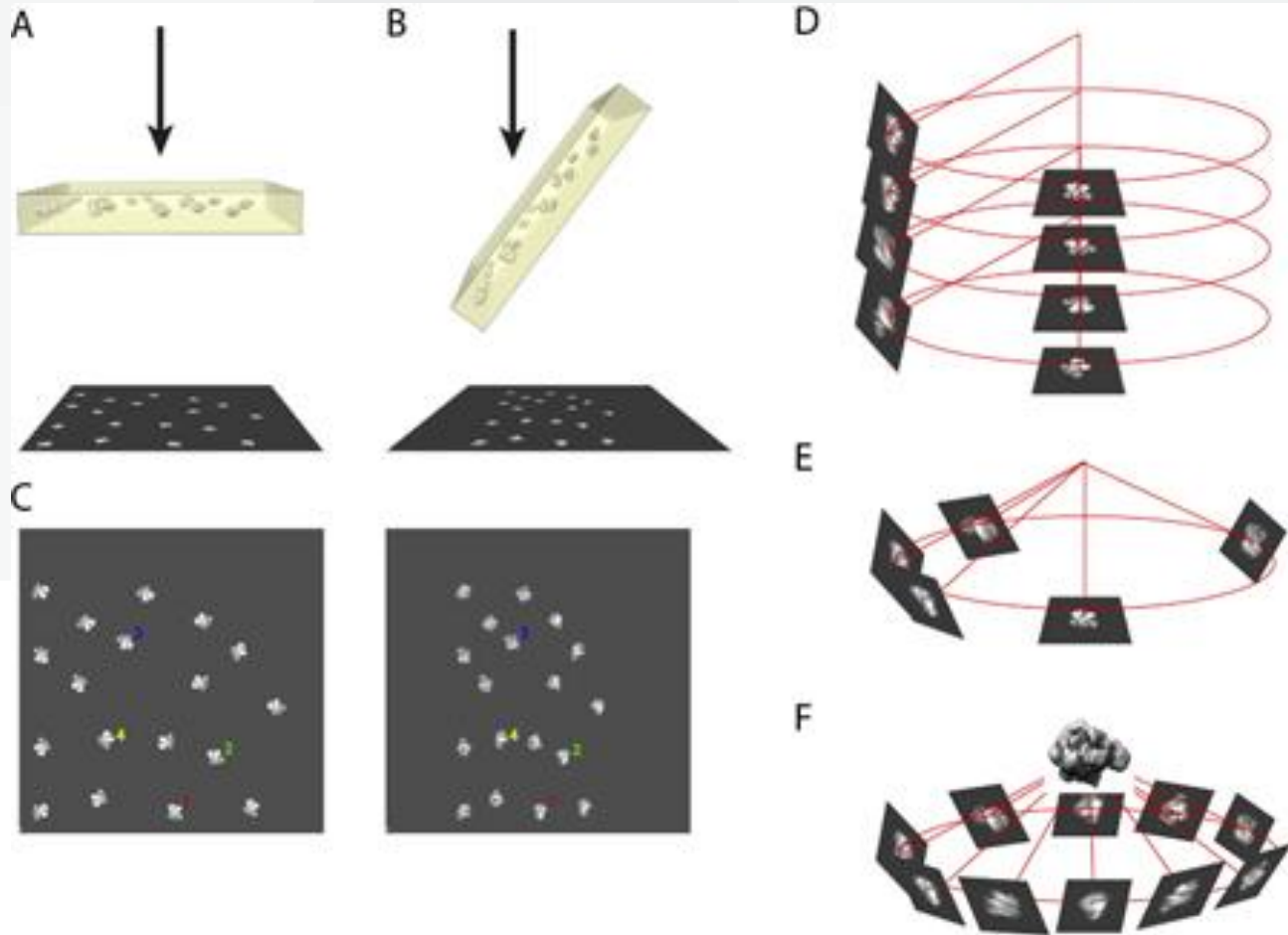
### Summary:

- 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 orientations of all three.



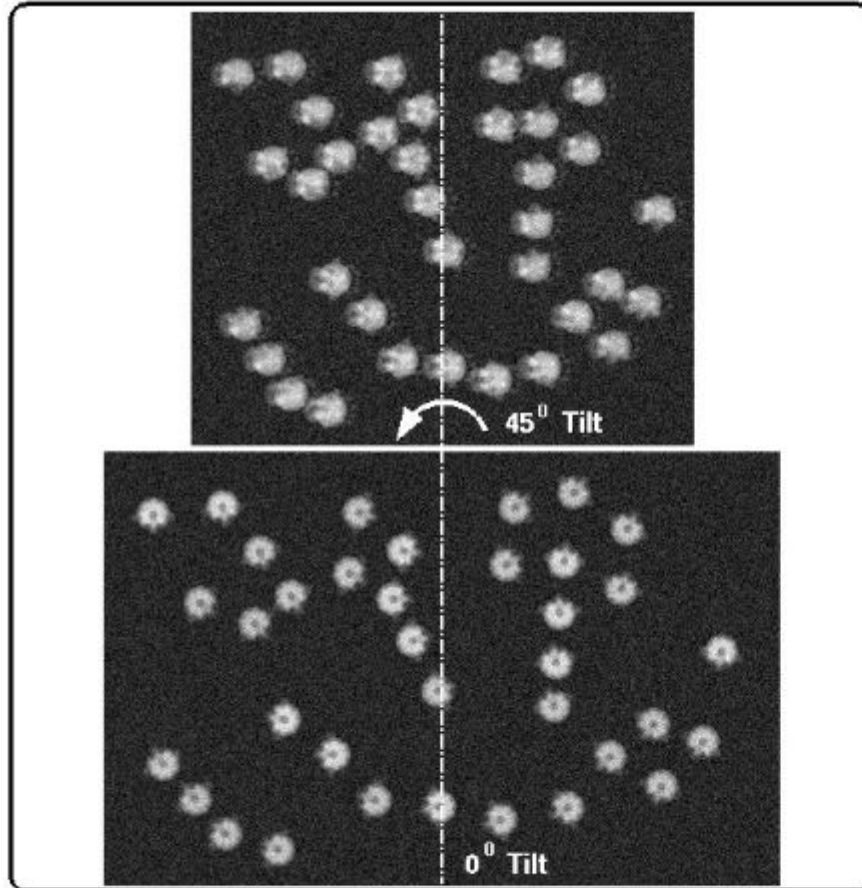
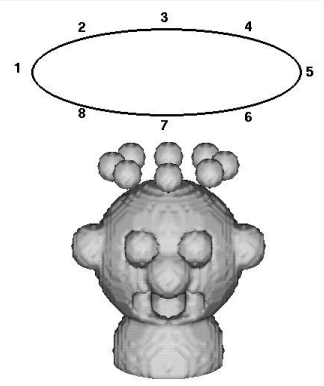
From Steve Fuller

# Random conical tilt





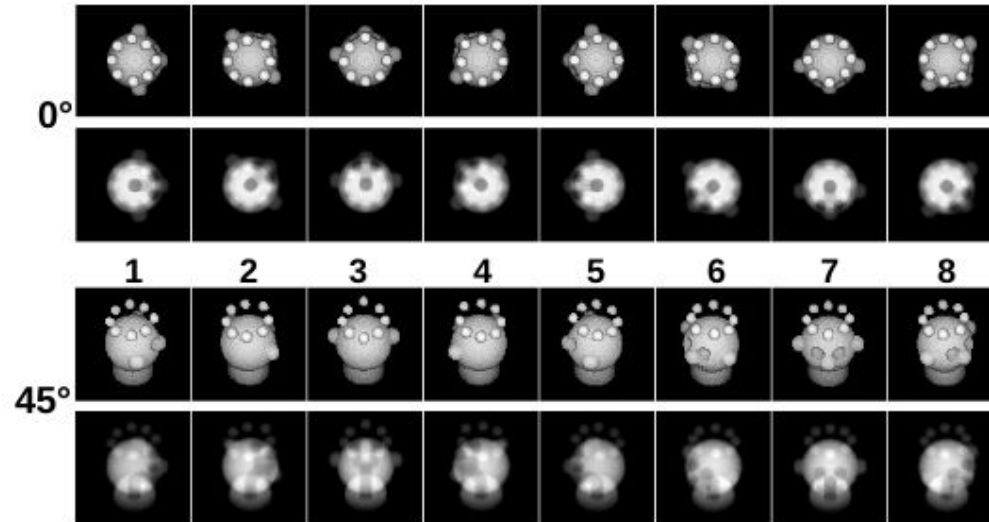
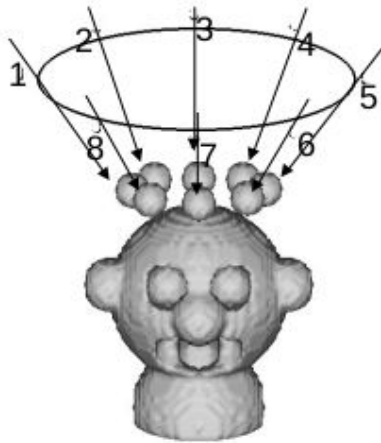
# Random conical tilt



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

# Random conical tilt

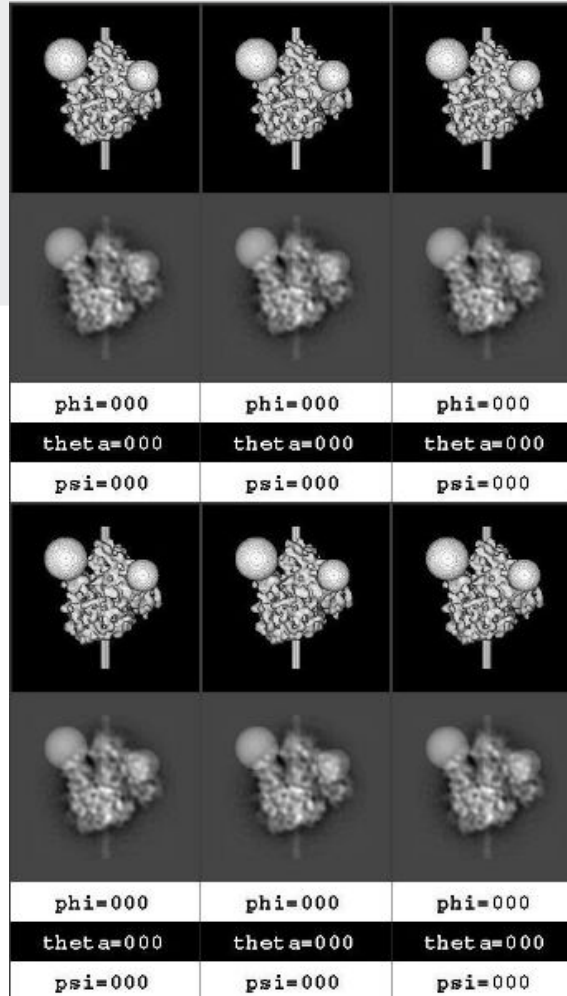
Two images are taken: one at  $0^\circ$  and one tilted at an angle of  $45^\circ$ .



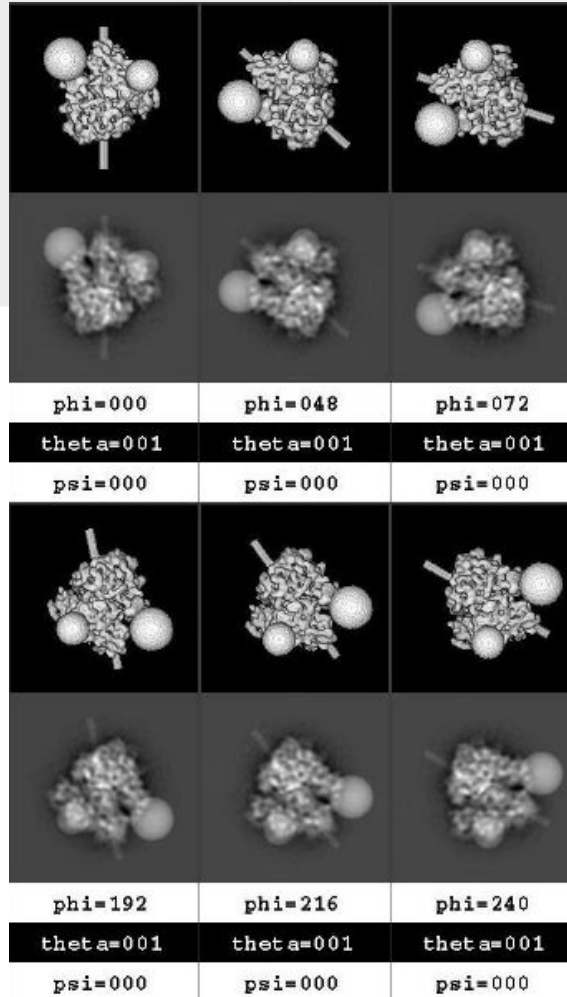
Radermacher, M., Wagenknecht, T., Verschoor, A. & Frank, J. Three-dimensional reconstruction from a single-exposure, random conical tilt series applied to the 50S ribosomal subunit of *Escherichia coli*. *J Microsc* **146**, 113-36 (1987).

From Nicolas Boisset

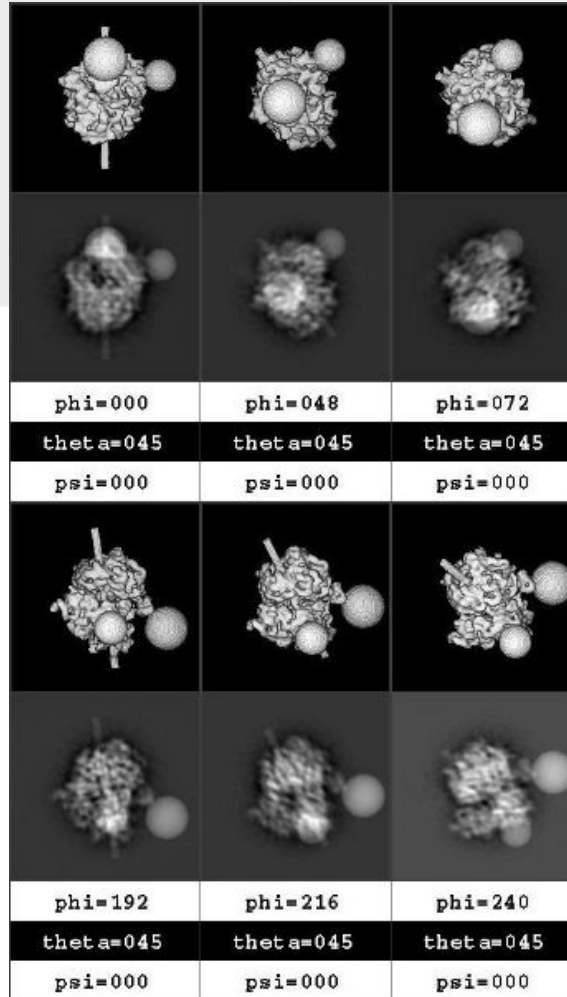
# Random conical tilt



# Random conical tilt



# Random conical tilt

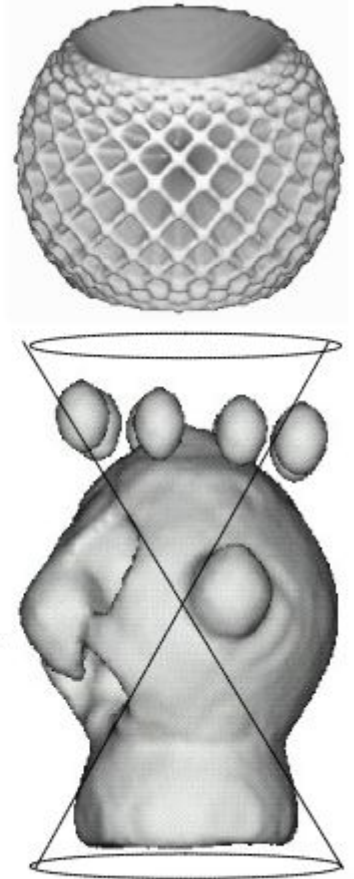


# Random conical tilt

- we cannot tilt the stage to 90 deg → “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.



# 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.

