# CEITEC 

Central European Institute of Technology
BRNO | CZECH REPUBLIC

## Image analysis II

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


## Outline

## Image analysis II

- Fourier transforms revisited
- Digitization
- Alignment
- Multivariate data analysis


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## Fourier transforms: Definition

$$
F(k)=\int_{-\infty}^{\infty} f(x) e^{-2 \pi i k x} d x
$$

f: function (1D) which we are transforming
$x$ : real-space coordinate
$i: \quad \sqrt{ }-1$
$k$ : spatial frequency
$F(k)$ : Fourier coefficient at frequency $k$

- complex, of the form $a+b i$


## Fourier transforms: Definition

$$
F(k)=\int_{-\infty}^{\infty} f(x) e^{-2 \pi i k x} d x
$$

Euler's Formula: $\quad e^{i \phi}=\cos \phi+i \sin \phi$
$F(k)=\int_{-\infty}^{\infty} f(x) \cos (-2 \pi k x) d x+i \int_{-\infty}^{\infty} f(x) \sin (-2 \pi k x) d x$

## Fourier transforms: Definition

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$$



Amplitude, A: $\sqrt{a^{2}+b^{2}}$
Phase, $\Phi: \quad \arctan \frac{b}{a}$

## Fourier transforms: plot of cosine of $x$



## 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.


## Fourier transforms: plot of sawtooth function


http://mathworld.wolfram.com

## How do we calculate the Fourier coefficients?

## Fourier transforms: Definition




Amplitude, A: $\sqrt{a^{2}+b^{2}}$
Phase, $\Phi: \quad \arctan \frac{b}{a}$

Why aren't we calculating the cosine terms?

## Fourier transforms: Sawtooth function



## Fourier transforms: plot of a Gaussian




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## Digitization in 2D



Digitization in 1D: Sampling


## Digitization: Is our sampling good enough?



Here, our sampling is good enough.

## Digitization in 1D: Bad sampling



## What's the best resolution we can get from a given sampling rate?



A 4-pixel "image"

In other words, what is the most rapid oscillation we can detect?

## What's the best resolution we can get from a given sampling rate?



> A 4-pixel "image"

In other words, what is the most rapid oscillation we can detect?
ANSWER: Alternating light and dark pixels.


The period of this finest oscillation is 2 pixels.
The spatial frequency of this oscillation is $0.5 \mathrm{px}^{-1}$.
The finest detectable oscillation is what is known as "Nyquist frequency."
The edge of the Fourier transform corresponds to Nyquist frequency.

## Nyquist frequency



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The finest detectable oscillation is what is known as "Nyquist frequency."
The edge of the Fourier transform corresponds to Nyquist frequency.

## What do we mean by pixel size?

Typical magnification: 50,000X Typical detector element: $15 \mu \mathrm{~m}$ (pixel size on the camera scale)

Pixel size on the specimen scale:
$15 \times 10^{-6} \mathrm{~m} / \mathrm{px} / 50000=$ $3.0 \times 10^{-10} \mathrm{~m} / \mathrm{px}=3.0 \AA / \mathrm{px}$

In other words, the best resolution we can achieve (or, the finest oscillation we can detect) at $3.0 \AA / p x$ is 6.0 A .


Transmission Electron Microscope
It will be worse due to interpolation,
http://www.en.wikipedia.org so to be safe, a pixel should be 3 X smaller than your target resolution.

## Interpolation



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

Effect of shifts

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

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

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


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

$\Delta x=\Delta y=0.40 p x$
$\Delta x=\Delta y=0.20 p x$

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

## Two more properties of Fourier transforms: Noise

- The Fourier transform of noise is noise
* "White" noise is evenly distributed in Fourier space
- "White" means that each pixel is independent


White noise

## Effects of interpolation are resolution-dependent




Suppose we rotate the image.
The new pixels will be weighted averages of the old pixels.


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


Power spectrum profile


$-0.0574127,0.000869291$


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

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（P）review of 3D reconstruction： The parameters required

Two translational：
$\Delta x$
$\Delta y$
Three orientational （Euler angles）：
${ }^{\gamma}$ phi（about $z$ axis）
$\checkmark$ theta（about $y$ ） psi about new $z$ ）

These are determined in 2D．


How do find the relative translations between two images?

## Translational alignment



Image $f$

$$
\sum^{16} f(\vec{x}) g(\vec{x})
$$

Cross-correlation coefficient: $\quad N=1$

$$
\overline{\sigma_{f}} \sigma_{g}
$$

## Cross-correlation coefficient

$$
\text { Cross-correlation coefficient: } \frac{\sum_{N=1}^{16} f(\vec{x}) g(\vec{x})}{\sigma_{f} \sigma_{g}}
$$

If the alignment is perfect, the correlation value will be 1.

What if the correlation isn't perfect?

## Translational alignment



Image $f$


Image $g$

What if the correlation isn't perfect?
ANSWER: You try other shifts (perhaps all).

## Cross-correlation function (CCF)

Brute-force translational search is CPU-intensive

## BUT

Fourier transforms can help us.

## Some notation:

$$
\text { Real space } \quad f(x) \quad g(x)
$$

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

$$
F^{*}(X) G(X)=F . T .(C C F)
$$

This gives us a map of all possible shifts.

## Cross-correlation function (CCF)



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

That was an easy case.
We only needed to do translational alignment.
What about orientation 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 <br> radius 3 radius 4 <br> 360



Image 2

Which do you perform first?
Translational or orientation alignment?

## Translational and orientation alignment are interdependent



Image 1


Image 2


Superimposed

SOLUTION: You try a set of reasonable shifts, and perform separate orientation alignments for each.

## 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.

Different alignment schemes

## Reference-based alignment



There's a problem with reference-based alignment:
Model bias

## Model bias



Reference


Images of pure noise

## Averages of images of pure noise


$N=128$

$N=1024$
$N=256$
$\mathrm{N}=512$

$N=2048$
original

There are reference-free alignment schemes

## Reference-free alignment (SPIDER command AP SR)



Single image picked randomly as reference

Disadvantage: Alignment depends on the choice of random seed.

## Pyramidal/pairwise alignment



Marco... Carrascosa (1996) Ultramicroscopy

You have aligned images, but they don't all look the same.


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


http://isomorphism.es

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



## Multivariate data analysis (MDA), or

 Multivariate statistical analysis (MSA)

Now, we have a 16-dimensional problem.

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



Suppose pixel 6 coincided with pixel 11, And pixel 7 coincided with pixel 10.
Then, we're back to two variables, and a 2D problem.

## 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.

Covariance of measurements $x$ and $y$ :

$$
\langle x y>-\langle x\rangle<y\rangle,
$$

where $\langle x\rangle$ is the mean of $x$.

A high covariance is a measure of the correlation between two variables.

## 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 cigenvectors 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 | － | ， |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| \％ | \％ | 暑 | ＊ | 3＊ | 4 | ＊ | \％ | ＊ | ＊ | ＊ |  |
| 4 | \％ | 新 | ＊ | ＊ | ＊ | ＊ | $\geqslant$ | \％ | \％ |  |  |
| 38 | ＊ | \％ | 4 | ＊ | 8 | ＊ | \％ | ＊ | \％ | ＊ |  |
| ） | ＊ | 楽 | \％ | \％ | \％ | \％ | \％ | 6） | \％ | \％ | ， |
| 6 | ＊ | 尔 | \％ | 27 | 3 | ＊ | \％ | ＊ | 8 | 3 |  |
| \％ | 3 | 8 | 8 |  |  |  |  |  |  |  |  |

PCA of worm hemoglobin

## Average:



Next week:
Classification \& 3D Reconstruction

## Thank you for your attention

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 Development for Innovation


## Some simple 1D transforms: a 1D lattice




## Some simple 1D transforms: a box


http://cnx.org

## Some simple 1D transforms: a Gaussian




## Some simple 1D transforms: a sharp point (Dirac delta function)


http://en.labs.wikimedia.org/wiki/Basic_Physics_of_Nuclear_Medicine/Fourier_Methods

## Some simple 2D Fourier transforms:

 a row of points
$\mathscr{8} \subset$ ㅌITEС

## Some simple 2D Fourier transforms: a 2D lattice



## Some simple 2D Fourier transforms: a sharp disc

# Some simple 2D Fourier transforms: <br> a series of lines 

