

Quantitative Big Imaging





About the Instructors

- Dr. Kevin Mader (mader@biomed.ee.ethz.ch)
- Lecturer at ETH Zurich
- Postdoc in the X-Ray Microscopy Group at ETH Zurich and Swiss Light Source at Paul Scherrer Institute









About the Instructors





About the Instructors

- Dr. Anders Kaestner (anders.kaestner@psi.ch)
- Group Leader at the ICON Beamline at the SINQ (Neutron Source)





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Exercises / Assistant

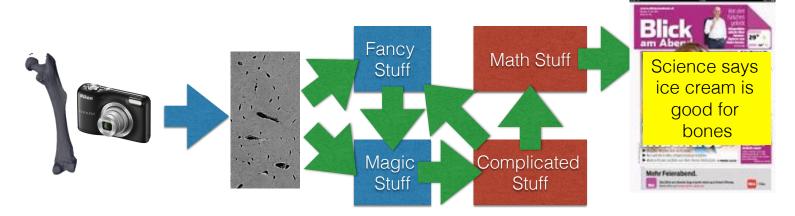


- Maria Büchner (maria.buechner@psi.ch)
- PhD Student in the X-Ray Microscopy Group at ETHZ and Swiss Light Source at Paul Scherrer Institute

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Motivation?



- To understand what, why and how from the moment an image is produced until it is finished (published, used in a report, ...)
- To learn how to go from one analysis on one image to 10, 100, or 1000 images (without working 10, 100, or 1000X harder)



Motivation?

Why does this class exist?

- Detectors are getting bigger and faster constantly
- Todays detectors are really fast
- 2560 x 2160 images @ 1500+ times a second = 8GB/s
- Matlab / Avizo / Python / ... are saturated after 60 seconds
- A single camera
 - More information per day than Dacebook*
 - Three times as many images per second as Instagram**

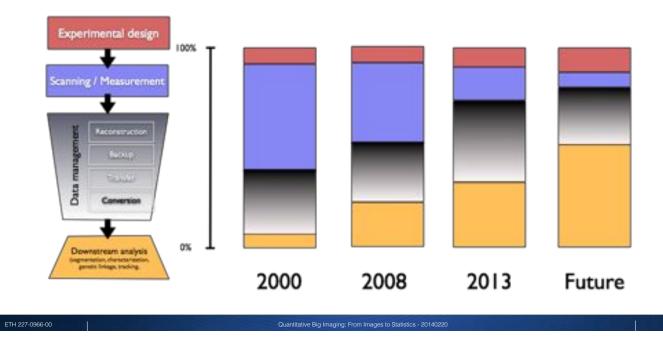
*http://news.cnet.com/8301-1023_3-57498531-93/facebook-processes-more-than-500-tb-of-data-daily/

http://techcrunch.com/2013/01/17/instagram-reports-90m-monthly-active-users-40m-photos-per-day-and-8500-likes-per-second/



Motivation?

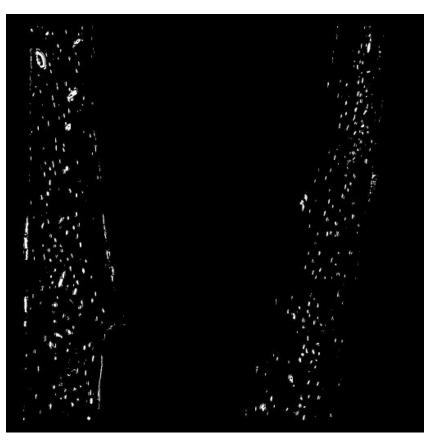
- In 2000 data acquisition (i.e. measuring) was slow
- Today it is 100-1000X faster
- The old analysis techniques are overwhelmed
- Computing has changed significantly





Overwhelmed?

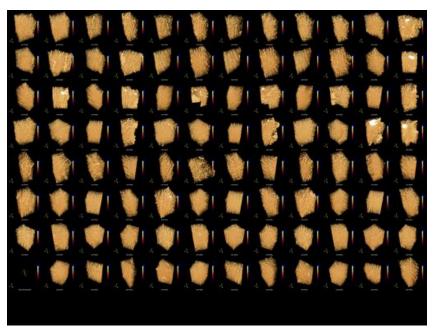
- Count how many cells are in the bone slice
- Ignore the ones that are 'too big' or shaped 'strangely'
- Are there more on the right side or left side?
- Are the ones on the right or left bigger, top or bottom?





Overwhelmed?

• Do it all over again for 96 more samples, this time with 2000 slices instead of just one!



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Overwhelmed?

Now again with 1090 samples!

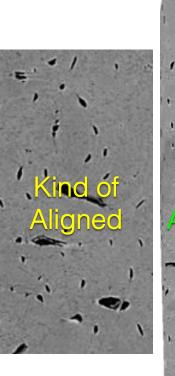


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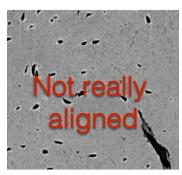


Overwhelmed?

- How aligned are these cells?
- Are they more or less aligned than these?
- or these?



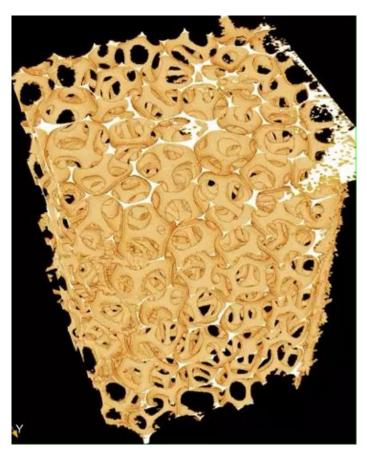






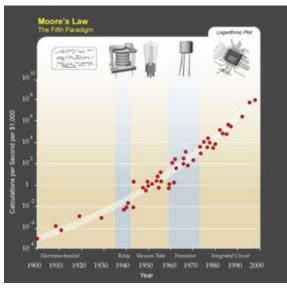
Overwhelmed?

- How many bubbles are here?
- How fast are they moving?
- Do they all move the same speed?
 - Do bigger bubbles move faster?
 - Do bubbles near the edge move slower?
- Are they rearranging?



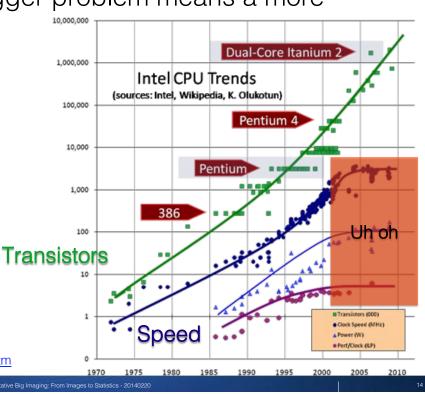
Computing has changed?

- Computers have traditionally become cheaper and faster at an astonishing rate
- Traditional solution: bigger problem means a more expensive computer



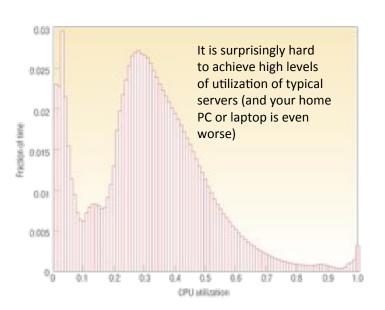
http://en.wikipedia.org/wiki/Moore's_law http://www.gotw.ca/publications/concurrency-ddj.htm

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Computing has changed?

- Computer, servers, workstations are wildly underused
- Buying a big computer that sits idle most of the time is a waste of money

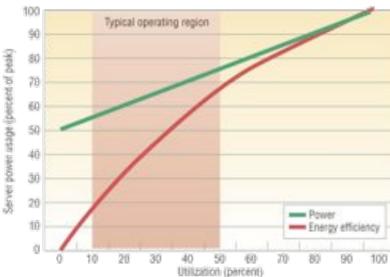


http://www-inst.eecs.berkeley.edu/~cs61c/sp14/ "The Case for Energy-Proportional Computing," Luiz André Barroso, Urs Hölzle, IEEE Computer, December 2007

Computing has changed?

• It is also energy inefficient

http://www-inst.eecs.berkeley.edu/~cs61c/sp14/ "The Case for Energy-Proportional Computing," Luiz André Barroso, Urs Hölzle, IEEE Computer, December 2007



Computing has changed?

- Traditionally the most important performance criteria was time, how fast can it be done
- With Platform as a service servers can be rented instead of bought
- Speed is still important but using cloud computing CHF / Gigabyte is the real metric





17



Course Outline

- 20th February Introductory Lecture
 - 27th February Filtering and Image Enhancement (A. Kaestner, HG E 26.3)
- 6th March Basic Segmentation, Discrete Binary Structures
 - 13th March Advanced Segmentation
 - 20th March Analyzing Single Objects
- 27th March Analyzing Complex Objects
- 3rd April Spatial Distribution
- 10th April Statistics and Reproducibility
 - 17th April Dynamic Experiments
- 8th May Big Data
 - 15th May Guest Lecture TbD
- 22th May Project Presentations

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Course Outline

- 27th February Filtering and Image Enhancement (A. Kaestner)
 - Noise / Artifact Sources, Spatial / Fourier-based Filtering, Morphology-based Filtering
 - Scale Space Filtering
 - Wavelets, Regularization-based Methods
- 6th March Basic Segmentation, Discrete Binary Structures
 - Science Motivation
 - Does my dinosaur fossil have teeth?
 - Project Selection / Team Formation
 - Histogram Evaluation, Selecting a threshold / resolution, Evaluating a/multiple thresholds, Using Region Growing Segmentation







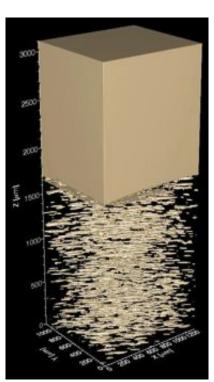
P. Donoghue et al., Nature 442, Aug. 2006



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Course Outline

- 13th March Advanced Segmentation
 - Science Motivation
 - Are these cells really connected and communicating?
 - Using Scale Space Techniques, Larger objects to surface details and substructures, Clustering, k-Means, Fuzzy methods, Boundary Identification, Automation, Regions of Interest, Subdividing Volumes
- 20th March Analyzing Single Objects
 - Science Motivation
 - How many cells, vessels, and cracks are in my bone?, How many bubbles are in my volcano?
 - Voxel Connectivity, Component Labeling / Filtering, Shape Tensor, Anisotropy, Oblateness, Isosurfaces, Meshing, Surface Area, Curvature





Course Outline

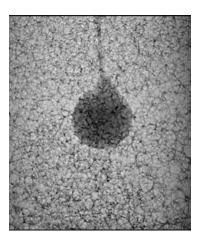
- 27th March Analyzing Complex Objects
 - Science Motivation
 - How many nodules are in my battery and how are they oriented? How does liquid move through the paint?
 - Distance Maps, Inter-object Distances, Relative Locations, Watershed, Segmenting connected structures, Thickness Analysis, Characterizing more complicated shapes, Skeletonization, Tortuosity, Networks
- 3rd April Spatial Distribution
 - Science Motivation
 - Where do bone cells get their nutrition from? Do cells align themselves to nearby vessels? Is there a pattern to pore distribution in rock?
 - Density, Image/Region Scale, Object Scale, Object Alignment, Image Scale, Local Scale, Nearest Neighbors, Clustering, Semi-crystalline Structures

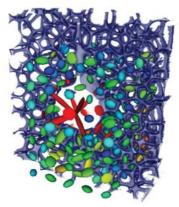
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Course Outline

- 10th April Statistics and Reproducibility
 - Science Motivation
 - Is this gene responsible for the cell size in bone? Does heating actually change the molten rock at all?
 - Parameter Screening, Script Writing, Unit Testing, Statistical Analysis, Plotting / Representing Data
- 17th April Dynamic Experiments
 - Science Motivation
 - How do these foam bubbles flow around this object / through this constriction? Does eruption cause a change in bubble shape?
 - Tracking voxels, surfaces, objects, topology



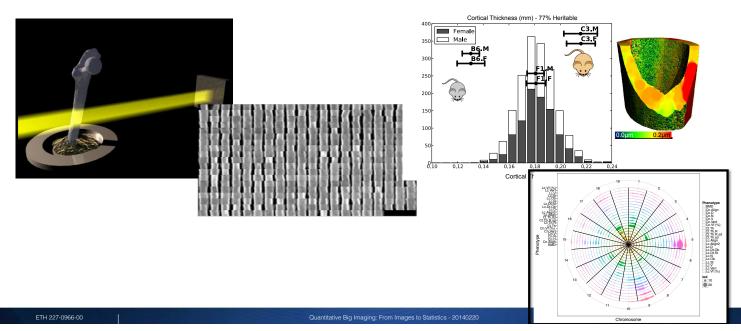


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Course Outline

- 8th May Big Data
 - Science Motivation
 - So I just measured 1300 samples and 2TB of data it's a mess, I started my analysis and it will take 3.5 years to finish
 - Databases, Clusters, Cloud Computing, MapReduce / Hadoop





Course Expectations

- 1 set of exercises per lecture
 - Easy Completing Matlab Scripts, using GUIs
 - Advanced Writing Python, Java, ...
- Science Project
 - Applying Techniques to answer scientific question
 - Choose from one of ours data or bring your own
 - Present approach, analysis, and results

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Outline – Lecture one

- History of Imaging
- Basic Definitions
- Imaging Techniques
- The need for quantitative metrics

• References

- Jean Claude, Morphometry with R, Online through ETHZ at <u>http://link.springer.com/book/10.1007%2F978-0-387-77789-4</u> Buy it at: <u>http://www.amazon.com/Morphometrics-R-Use-Julien-Claude/dp/ 038777789X</u>
- John C. Russ, "The Image Processing Handbook", Boca Raton, CRC Press Available online within domain ethz.ch (or proxy.ethz.ch / public VPN) <u>http://dx.doi.org/10.1201/9780203881095</u>

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History of Imaging

- 1840 photographic film (L. Daguerre, France, W. Talbot, USA),
- 1895 first public motion picture presentation (Lumiere brothers, France),
- late 1920s motion picture with sound,
- 1930s color movies,
- 1960s multichannel sound,
- 1970s huge-screen cinema (increased field of view), Imax Corp., Canada,
- 1999 e-cinema (digital storage and electronic projection), USA

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History of Imaging

- 1920s first TV experiments (Nipkov disk),
- early 1930s experimental TV broadcasting (New York, USA),
- 1939 first regular B/W TV service (USA),
- 1954/67 introduction of color TV in the US/Europe,
- 1970s video cassette recorder (VCR),
- early 1980s consumer laser disk player (analog),
- late 1980s analog direct broadcasting by satellite (Europe),
- mid 1990s digital direct broadcasting by satellite (US),
- late 1990s high-definition (digital) TV introduced in the US,
- 2000s digital cameras, video streaming, video cell phones, ...

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Lessons from history

- Very rapid acceleration of the use of imaging technologies in the last two decades.
- Turning point: introduction of digital capture, transmission and storage of images.
- New applications of imaging are likely to arise in the near future due to:
 - continuing advances in digital capture (multi-modal, multi-view, multifocus, ...),
 - rapidly increasing transmission, storage, and analysis capabilities (Big Data),
 - flexibility in manipulating digital images as compared to
 - increase accessibility of data (YouTube, flickr, Google Images) at little to no cost

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Challenges

- 3-D visual communications: presenting 3-D information
- Visual surveillance: extraction of statistics, anomalies from visual data.
- Visual databases: retrieval of images/video based on content (color, shape) instead of meta-data (keywords).
- Simplification: condensing thousands of images into simple easily understood data

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How to represent an image?

- Tuple: A list / collection values
 - (1,2,3) unlabeled
 - (x: 1, y: 1, val: 5.0) labeled
- Point: A position and one (or more) quantities of interest
 - (pos: (1,0), val: 1.0)
- Image: A lattice of points
- Sparse Image: A collection of points

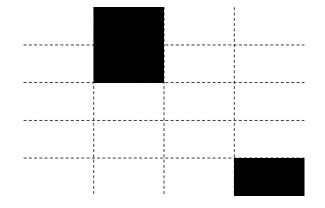
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2D Image

- I x J points
 - (x,y) position
 - val A numerical value

Image Representation



List Representation

x	У	val
0	0	0
1	0	1
0	1	0
1	1	1
L	J	1

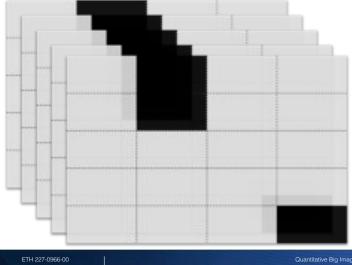
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3D Image

- I x J x K points
 - (x,y,z) position
 - val A numerical value

Image Representation: Collection of 2D images



List Representation

x	У	Z	val
0	0	0	0
1	0	0	1
0	1	0	0
1	1	0	1
I.	J	K	1

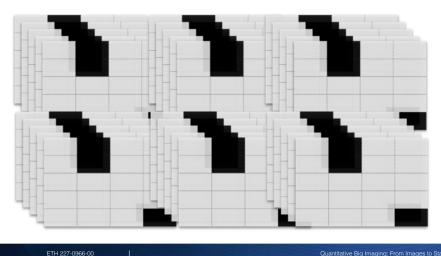
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4D Image

- I x J x K x M points
 - (x,y,z,t) position
 - val A numerical value

Image Representation: Collection of 3D images



List Representation

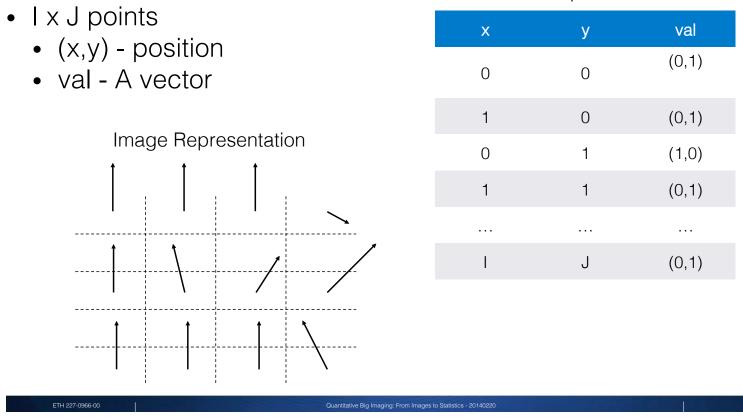
x	У	Z	t	val
0	0	0	0	0
1	0	0	0	1
0	1	0	0	0
1	1	0	0	1
I	J	К	М	1



Beyond Simple Images

- A point can represent one or more quantities of interest, what else can be represented in an image?
 - color -> 3 values (red, green, blue)
 - vector / orientation -> 2/3 values
 - tensor -> 9 values
 - spectrum -> many values (thousands)

2D Vector Image (Field)



List Representation

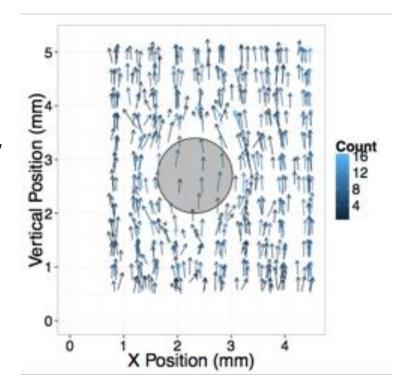
2D Tuple Image

	List Representation		
	X	у	val
 I x J points (x,y) - position val - A vector 	0	0	(val: 4, col: 'red', vel: (0,1,2))
	1	0	(val: 4, col: 'red', vel: (0,1,2))
Image Representation	0	1	(val: 4, col: 'red', vel: (0,1,2))
	1	1	(val: 4, col: 'green', vel: (0,1,2))
	I	J	(val: 4, col: 'black', vel: (0,1,2))
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2D Vector Image (Field)

- Commonly used to show flow
- Each arrow represents the average flux and direction inside each box



FFT



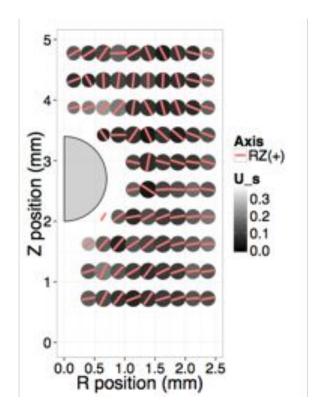
2D Tensor Image

List Representation		
x	у	val
0	0	[[1.0,0.1,0] [0,0.5,0] [0,0,1]]
1	0	
I	J	[[-1.0,0.1,0] [0.1,0.3,0] [.2,0,.7]]
	x D 1	x y D 0 1 0

List Representation

2D Tensor Image (bubbles around and obstacle, 2D view)

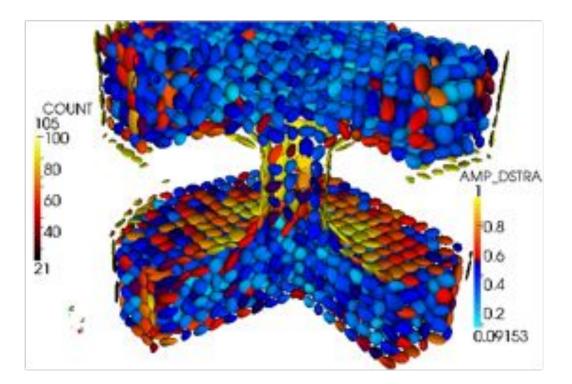
- Can be used to show deformation inside a system
- A circle is unperturbed and the more anisotropic the circle is the higher the deformation forces are inside each box
- Us= strain tensor
- Rz=orientation of the main axis



EE



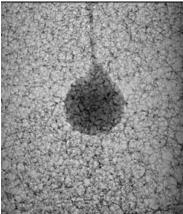
3D Tensor Image (bubbles through a conduit)



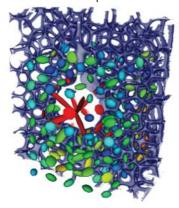
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Foam rheology in 3D: complex quantification

Wet, liquid foam



Strain tensor quantification

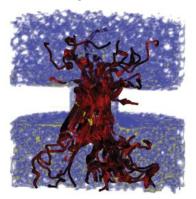


Flow around obstacle

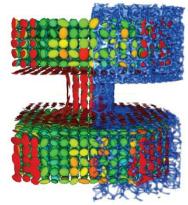
K. Mader, PhD thesis, 2013

Stampanoni - MaxIV Imaging Workshop - Kolle Kolle, Copenhagen, Danemark

Flow through constriction



Strain tensor quantification



Tuesday, May 13th 2013

2D spectral image (hyperspectral imaging)

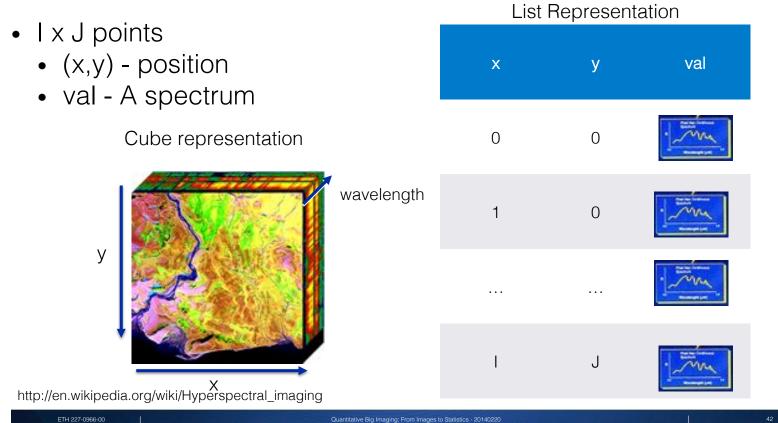


Image Formation

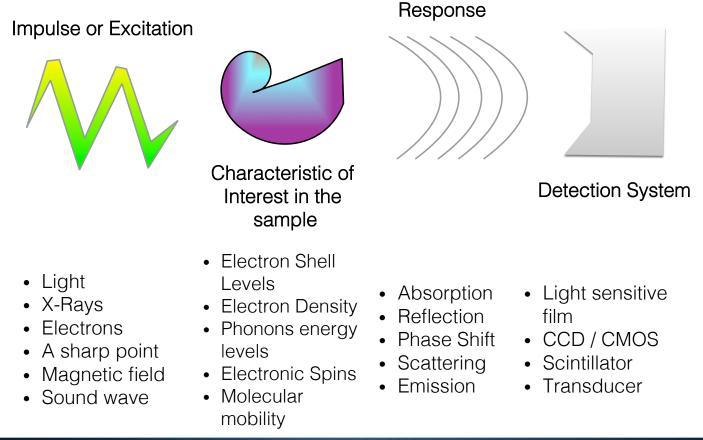


Image Formation VV



Response

Modality	Impulse	Characteristic	Response	Detection
Light Microscopy	White Light	Electronic interactions	Absorption	Film, Camera
Phase Contrast	Coherent light	Electron Density (Index of Refraction)	Phase Shift	Phase stepping, holography, Zernike
Confocal Microscopy	Laser Light	Electronic Transition in Fluorescence Molecule	Absorption and reemission	Pinhole in focal plane, scanning detection
X-Ray Radiography	X-Ray light	Photo effect and Compton scattering	Absorption and scattering	Scintillator, microscope, camera
Ultrasound	High frequency sound waves	Molecular mobility	Reflection and Scattering	Transducer
MRI	Radio-frequency EM	Unmatched Hydrogen spins	Absorption and reemission	RF coils to detect
Atomic Force Microscopy	Sharp Point	Surface Contact	Contact, Repulsion	Deflection of a tiny mirror

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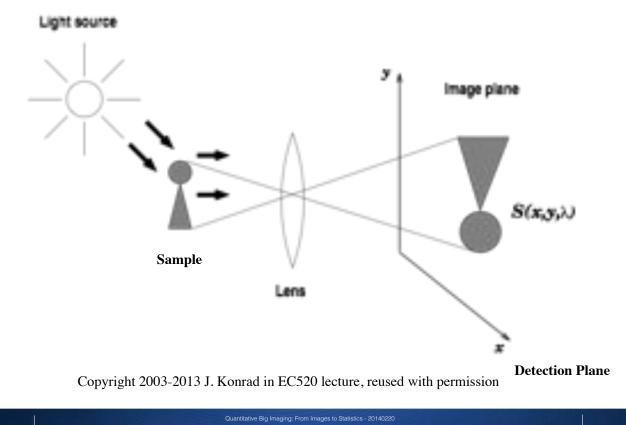
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Where do images come from?

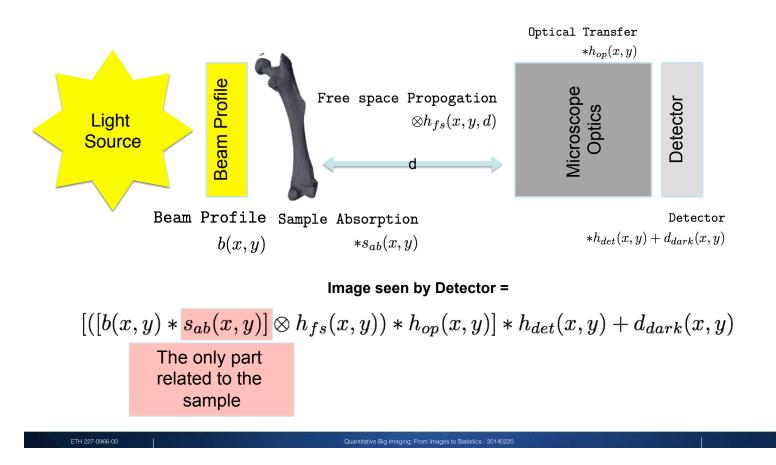
- Traditional / Direct imaging
 - Visible images produced or can be easily made visible
- Indirect / Computational imaging
 - No visible image to the eye
 - Response must be recorded and transformed to produce an image on a screen

Where do images come from?



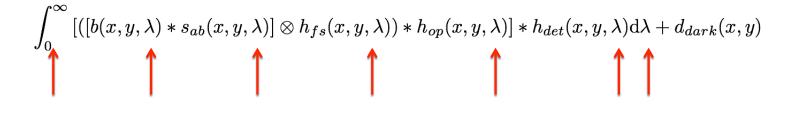
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Where do images come from?





Polychromaticity



- For polychromatic light, the frequency dependence of each component must be accounted for
- Significantly complicates problem of imaging
- Makes reverse problem (recovering information about the sample from the image) more difficult
- Makes monochromatic experiments extremely desirable!

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Basic Definitions

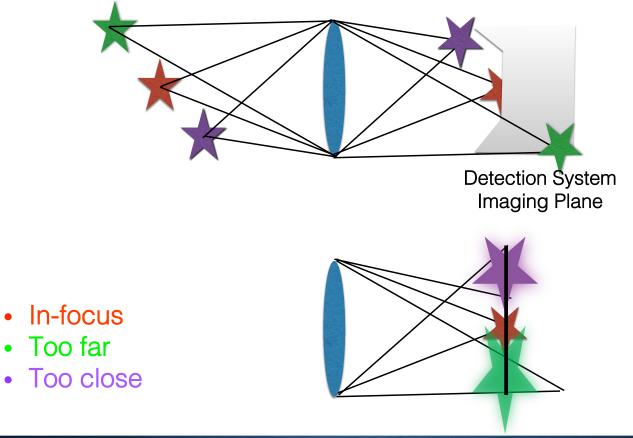
- Radiation process of emitting or transferring radiant energy.
- Radiant energy energy propagated in the form of electromagnetic waves
- Monochromatic radiant energy radiant energy of a single frequency.
- Photon elementary quantity of radiant energy of one frequency.
- Visible Light radiant energy evaluated with respect to its ability to stimulate the sense of sight of a human observer. Wavelength range: 350-780 nm.

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Traditional 3D Images

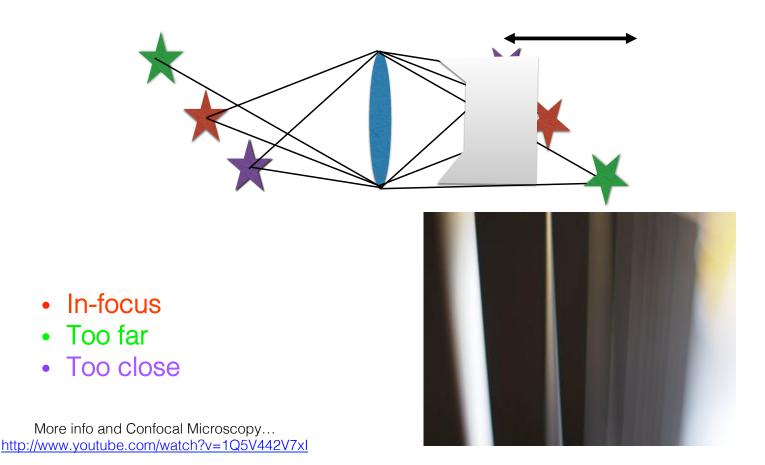


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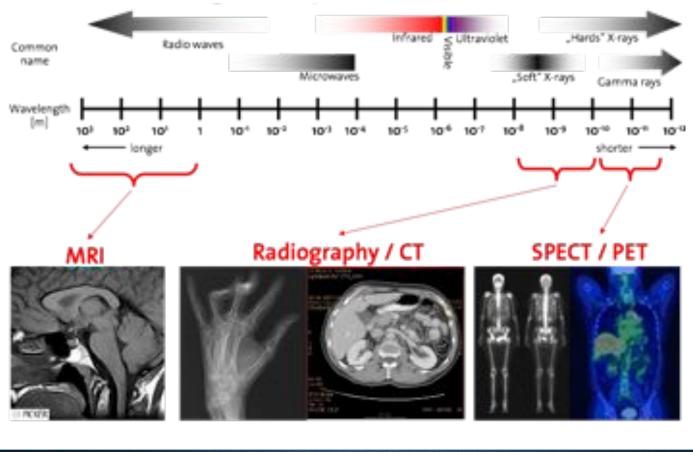
Focus Stacking → 3D



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Electromagnetic Spectrum



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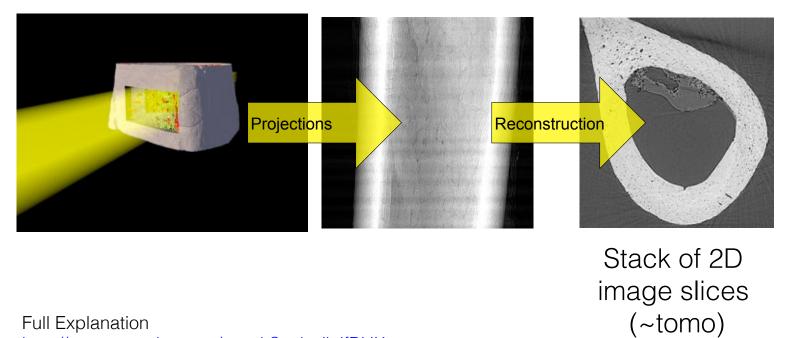
Where do images come from?

- Traditional / Direct imaging
 - Visible images produced or can be easily made visible
- Indirect / Computational imaging
 - Tomography through projections
 - Diffraction patterns
 - Surface Topography with cantilevers (AFM)
 - Hyperspectral imaging with Raman, IR, CARS
 -

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Quick Example http://www.youtube.com/watch?v=lgW84i-aUmM

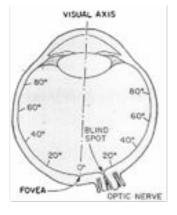


Full Explanation http://www.youtube.com/watch?v=bgjkJfBHKxg

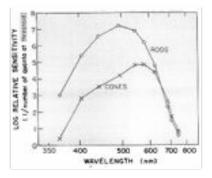
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Why do we need quantitative metrics?

- Human vision is great but far from perfect
- Good at some tasks
 - Seeing patterns and trends
 - Detecting artifacts and erroneous data
 - Removing noise
- Bad at other things
 - Blind spots
 - Interpreting color
 - Situational dependent performance
 - Counting many things
 - Biased



(III)

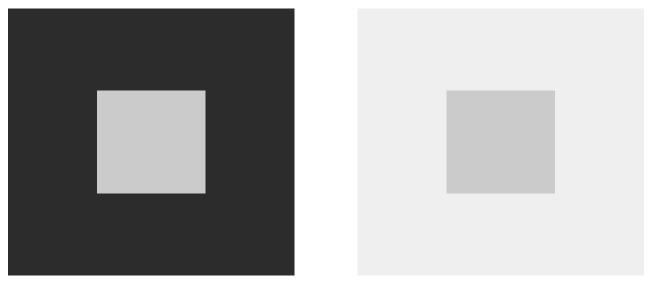


B. Wandell, Foundations of Vision, 1995

Why do we need quantitative metrics?

• Situational dependent performance

Which center square seems brighter?



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Why do we need quantitative metrics?

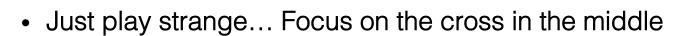
• Situationally dependent performance

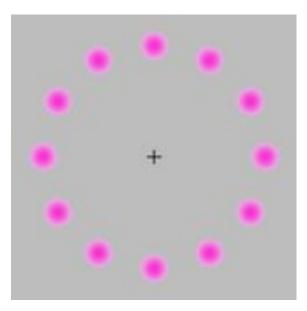
Are the bands uniform in brightness?



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Why do we need quantitative metrics?





The green blob only appears when you focus on the middle... What if instead of a green blob it's a tumor?

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Why do we need quantitative metrics?

 Biased - Many types: confirmation, contextual, interpretive

Context

Doctor's who have in the past seen more cases of a given disease are more likely to diagnose it in future cases Decisions are based on context rather than statistics and presenting the same information to multiple doctor's elicits multiple responses

Egglin, T. K., & Feinstein, A. R. (1996). Context bias. A problem in diagnostic radiology. JAMA : the journal of the American Medical Association, 276(21), 1752–5.