Image Analysis

...or what happens after the experiment?

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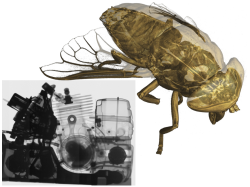


Outline

Introduction

3D and 4D imaging produce large amounts of data

Gigabytes. . .
. . . or even
terabytes of data

- 3D visualization
- Sample characteriztation
- Process parameterization
- etc

What do you want to know from the data?

Quantitative

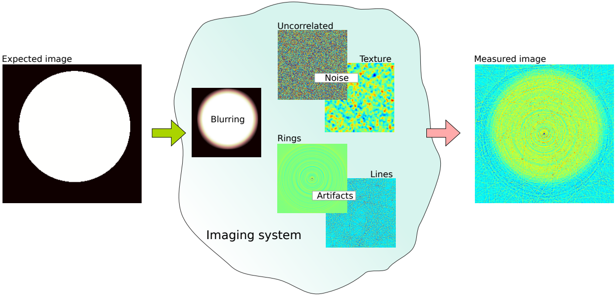
- Material composition
- Material transport

Structure

- Identify items
- Item geometry

This will affect the choice of processing methods.

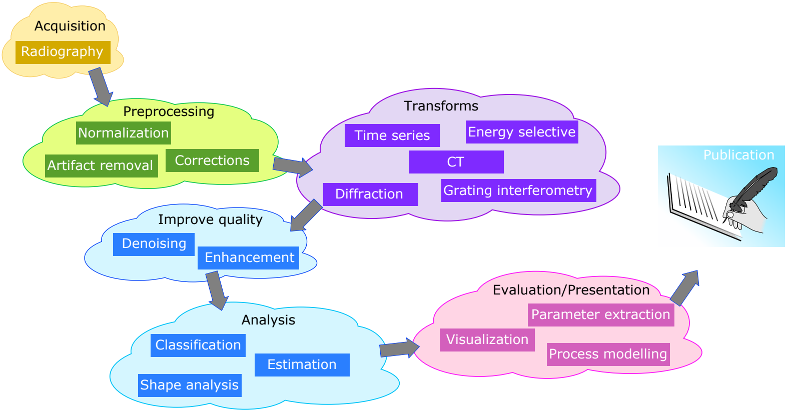
Measurements are rarely perfect



Factors affecting the analysis

- Resolution
- Small relevant features
- Sample movement
- Noise
- Inhomogeneous contrast
- Artefacts

A typical processing chain



Different types of images

2D

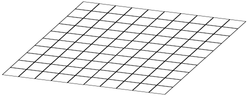
- Pictures
- Radiographs
- CT slices

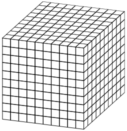
3D

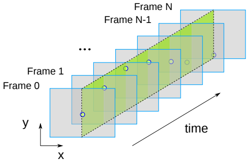
- Volumes
  x, y, z
- Movies
  x, y, t

4D

- Volume movie
  x, y, z, t







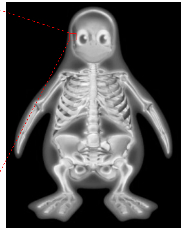
The smallest elements of an image

Definition

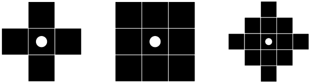
A pixel is the smallest element of an image. It has

- intensity and color
- a position in the image
- in 3D it is called voxel

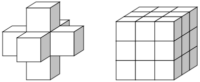
83	104	124	120	94	67	79	83	92	100
84	104	124	123	98	69	78	84	92	100
85	104	124	126	103	72	77	84	91	102
86	102	123	129	107	76	78	84	92	109
86	101	122	130	112	81	80	86	96	118
86	102	121	132	116	84	82	88	99	125
84	101	124	134	123	91	88	87	103	132
84	100	123	133	124	94	90	90	106	136
84	99	122	133	128	100	93	93	109	140
83	98	120	132	133	105	95	95	110	142



2D – Pixel neighborhoods



3D – Voxels neighborhoods

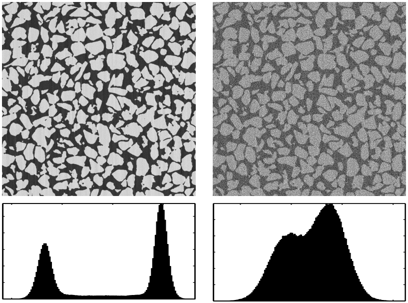


The histogram

The histogram is a statistical representation of the pixel intensities.
It plots the frequencies of the gray levels in the image

It can be used as

- performance indicator for experiment setup.
- guide for the *visualization*.
- base for *segmentation* methods.



Data types

Integers ...

- Can only represent integers (0, 1, 2, 3, ...).
- Either signed or unsigned.
- Raw format from camera

Examples

$$\frac{25}{100} = 0 \qquad \frac{100}{4} = 4$$

Floating point ...

- Can represent real numbers.
- Should be used for most calculations $\rightarrow$ type casting.
- Require more storage space

Examples

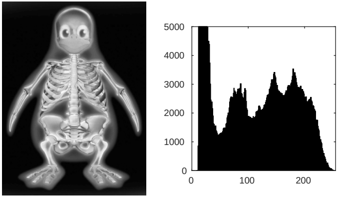
$$\frac{25}{100} = 0.25 \qquad \frac{100}{4} = 4.0$$

Bits and dynamics

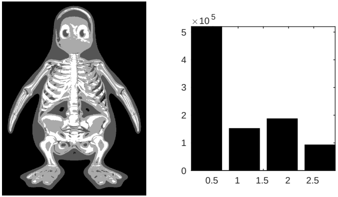
Dynamics and sensitivity

- Images are stored in 8- or 16-bit format.
- Great contrast differences require more bits.
- The sensitivity to small changes require more bits.

8 bit - 256 gray levels



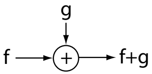
2 bit - 4 gray levels



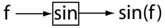
Basic operations

A pixel wise operator performs the same operation on each pixel in the image

Binary operations $c(\mathbf{x}) = a(\mathbf{x})\,\mathrm{op}\,b(\mathbf{x})$



Unary operations $b(\mathbf{x}) = op(a(\mathbf{x}))$



Examples are

- Arithmetic operators (addition, subtraction, multiplication, and division)
- Any scalar function (sin, cos, log, exp, etc)

Pixel-wise operations are often written without the index $\mathbf{x}$

Looking into Beer-Lamberts law

The intensity of a neutron radiograph is described by

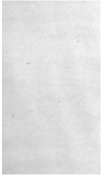
$$I = I_0 e^{-\int_L k(x)\,dx}$$

We measure

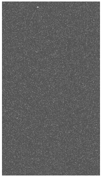
Sample

$I =$ 

Open beam

$I_0 =$ 

Dark current

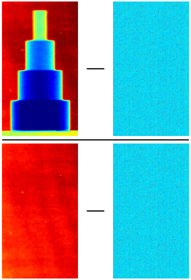
$I_{DC} =$ 

Compensation for camera background

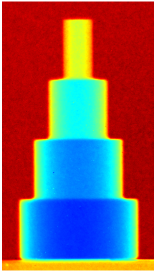
Open beam correction

From Beer-Lamberts law, $I = I_0 e^{-\int_L k(x)\,dx}$, we get

$$p = \frac{I - I_{DC}}{I_0 - I_{DC}} =$$



$=$



- p Normalized projection
- I Measured radiographic image
- I_{OB} Open beam image – the beam + scintillator profile
- I_{DC} Dark current image – bias introduced by camera

Open beam correction – Error propagation

No measurement is error free

- Intensities are random variables (Poisson distribution).
- Artifacts result in intensity variations

$$p = \frac{(I+\epsilon_I)-(I_{DC}+\epsilon_{DC})}{(I_0+\epsilon_0)-(I_{DC}+\epsilon_{DC})} \tag{1}$$

Improve image quality by acquisition

For a given exposure time and pixel size:

ϵ_I Change acquisition parameters

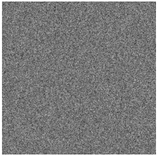
ϵ_0 Acquire many to improve statistics

ϵ_{DC} Acquire many to improve statistics

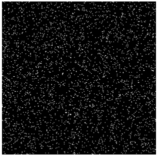
Noise

Noise types

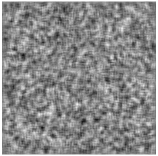
Gaussian



Salt 'n pepper

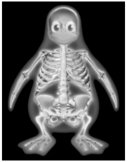


Textured

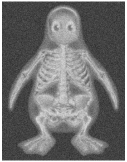


Signal to noise ratio

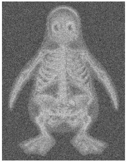
$$SNR = \frac{\mu}{\sigma}$$



SNR=∞



SNR=10



SNR=5

SNR=2

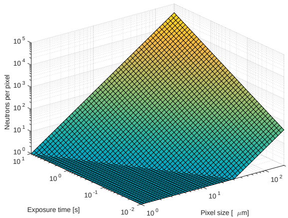
Neutron statistics – What can we expect?

Neutrons per pixel vs SNR

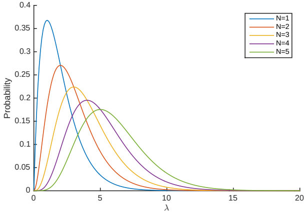
The average number of neutrons N reaching the detector.

$$SNR \sim \sqrt{N} = \sqrt{\underbrace{flux[n\, cm^{-2} s^{-1}]}_{constant} \times \underbrace{area[cm^2] \times time[s]}_{variable}} \qquad (2)$$

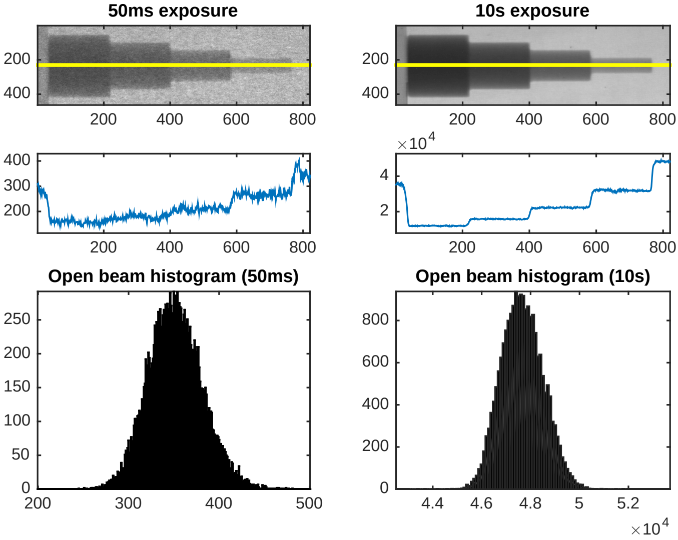
Pixel size and exposure time



Poisson distribution



Noisy profiles



The importance of good reference data

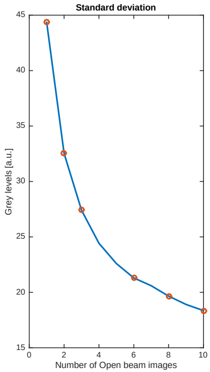
$$p = \underbrace{(I+\epsilon_I)-(I_{DC}+\epsilon_{DC})}_{\text{Variable}} \Big/ \underbrace{(I_0+\epsilon_0)-(I_{DC}+\epsilon_{DC})}_{\text{Constant}} \qquad (1 \text{ revisited})$$

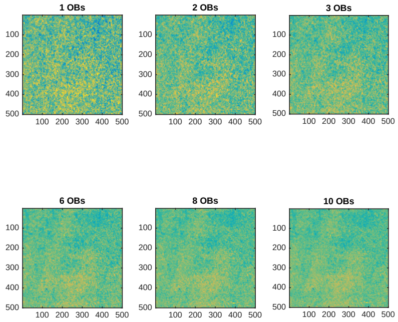
Sensitive cases

- Low dose acquisition
  Low SNR as it is, why make it worse?
- Computed tomography
  $\epsilon_0 + \epsilon_{DC}$ is repeated for all projections $\rightarrow$ rings.

How many open beam image are needed?

Exposure 100 ms





Summary - introduction

- Rule of thumb – at least 5 OBs more are better.
- Many OBs have greatest impact for low dose cases.
- Risk to introduce outliers with many references.

$$\Downarrow$$

- Spend more time on good reference data.
- Use outlier removal on reference data as standard procedure.

Image enhancement

Noise suppression using a filter

Definition

A filter is a process that alters the image to either suppress or enhance information using a set of neighborhood pixels.

Mainly two types:

- Linear spatially invariant filters. Computed with convolution
- Non-linear filters

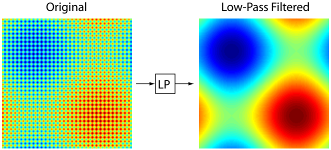
Books that cover filters are e.g. Jähne [2002] or Jain [1989]

Filter characteristics

Low pass filters

- Slow changes are enhanced
- Rapid changes are suppressed

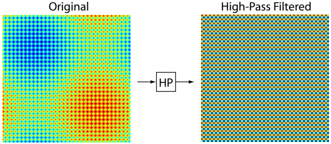
Example: Noise reduction



High pass filters

- Rapid changes are enhanced
- Slow changes are suppressed

Example: Feature detection



Linear filters

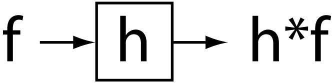
Computes filter operation using the convolution operation

$$g(\mathbf{x}) = h * f(\mathbf{x}) = \int_{\Omega} f(\mathbf{x}-\boldsymbol{\tau})\, h(\boldsymbol{\tau})\, d\boldsymbol{\tau} \tag{3}$$

$$g(\mathbf{x}) = h * f(\mathbf{x}) = \sum_{p \in \Omega} f(\mathbf{x}-\mathbf{p})\, h(\mathbf{p}) \tag{4}$$

where

- $f(\mathbf{x})$ is the image
- h is the convolution kernel of the filter



Low-pass filters

Low-pass filters have an averaging effect that suppress noise.

Mean or Box filter

All weights have the same value.

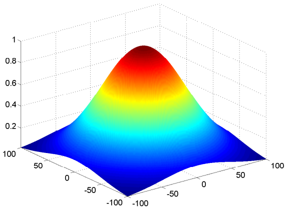
Example:

$$B = \frac{1}{25} \cdot \begin{array}{|c|c|c|c|c|} \hline 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 \\ \hline \end{array}$$

Gauss filter

$$G = e^{-\frac{x^2+y^2}{2\,\sigma^2}}$$

Example:



Using a Mean filter

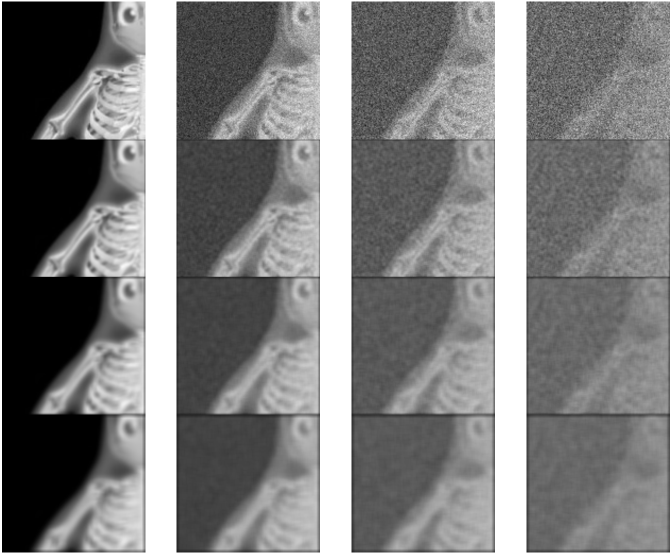
No noise SNR=10 SNR=5 SNR=2

No filter

σ=3

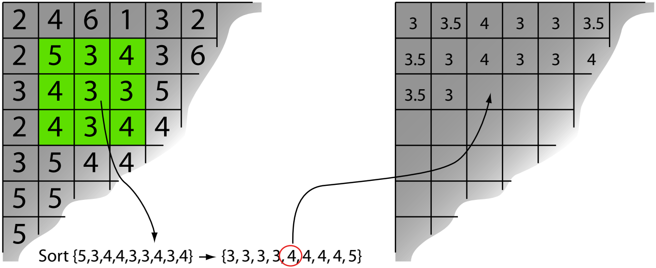
σ=5

σ=7



The median filter

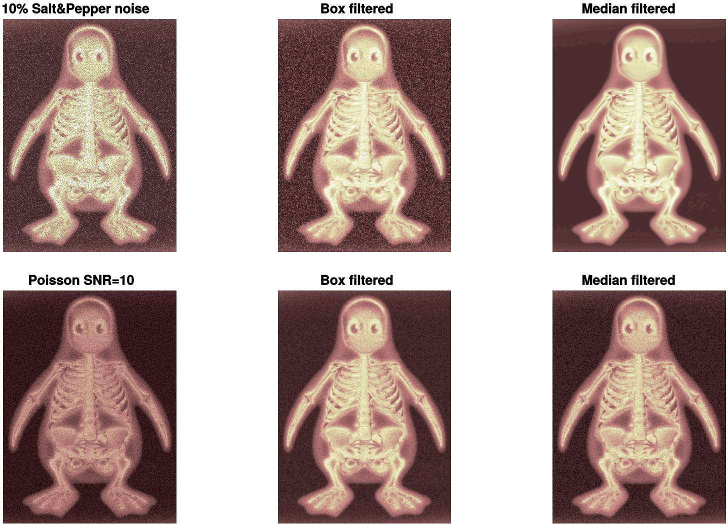
Principle



Features

- Low pass type
- Good at removing local outliers
- Gentle to edges

Comparing filters



High-pass filters

High-pass filters enhance rapid changes – ideal for edge detection

Typical high-pass filters:

Gradients

$$\frac{\partial}{\partial x} = \frac{1}{2} \cdot \begin{array}{|c|c|}\hline -1 & 1 \\ \hline\end{array}$$

$$\frac{\partial}{\partial x} = \frac{1}{32} \cdot \begin{array}{|c|c|c|}\hline -3 & 0 & 3 \\ \hline -10 & 0 & 10 \\ \hline -3 & 0 & 3 \\ \hline\end{array}$$

Laplacian

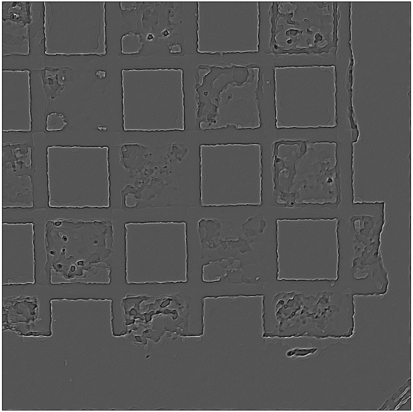
$$\triangle = \frac{1}{2} \cdot \begin{array}{|c|c|c|}\hline 1 & 2 & 1 \\ \hline 2 & -12 & 2 \\ \hline 1 & 2 & 1 \\ \hline\end{array}$$

Sobel

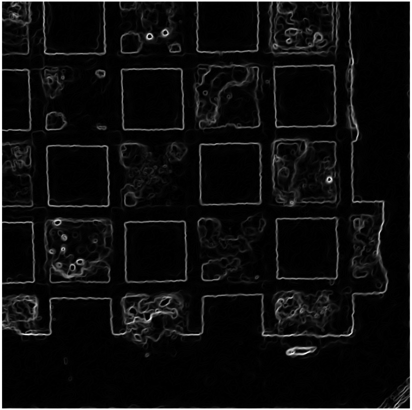
$$G = |\nabla f| = \sqrt{\left(\frac{\partial}{\partial x} f\right)^2 + \left(\frac{\partial}{\partial y} f\right)^2}$$

Filters for edge detection

Laplacian



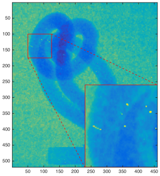
Sobel



Filter example: Spot cleaning

Problem

- Many neutron images are corrupted by spots that confuse following processing steps.
- The amount, size, and intensity varies with many factors.



Solutions

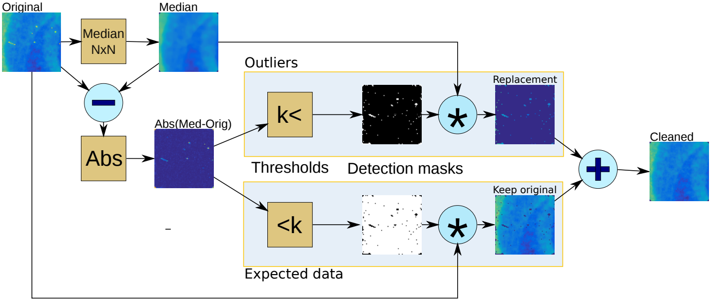
:-(Low pass filter

:-(Median filter

:-) Detect spots and replace by estimate

Spot cleaning algorithm

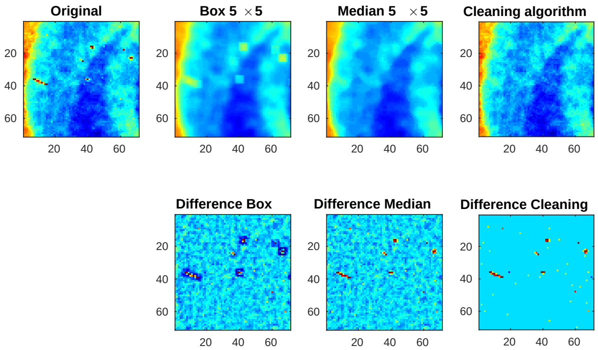
An algorithm



Parameters

- N Width of median filter.
- k Threshold level for outlier detection.

Spot cleaning – Compare performance



The ImageJ ways

Despeckle Median ... please avoid this one!!!

Remove outliers Similar to cleaning algorithm

Advanced non-linear filters for noise suppression

Motivation

Basic filters have problems to handle

- Low SNR
- Textured noise
- Edges

Something new is required...

The solution

Partial differential equation based filters
can take noise suppression one step further.

PDE based filters

Non-linear diffusion

Smooth fine features first

$$\frac{\partial u}{\partial t} = \underbrace{G(|\nabla_\sigma u|)}_{\text{Diffusivity}} \nabla^2 u$$

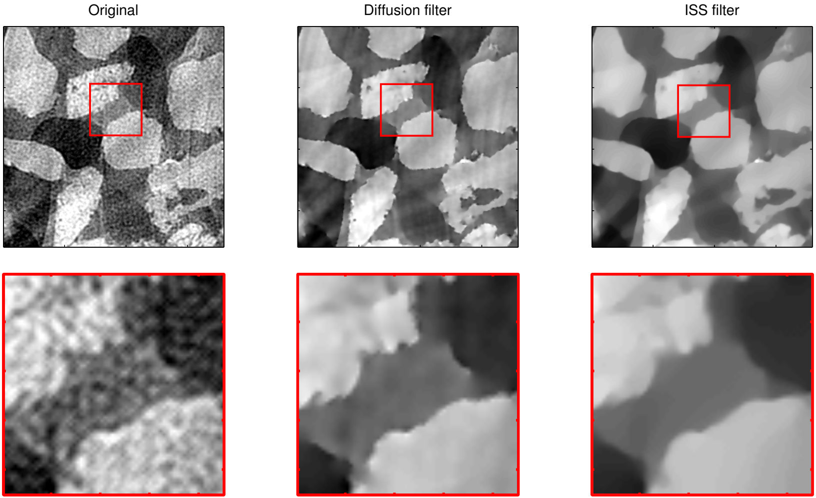
Inverse scale space

Add wide features first

$$\frac{\partial u}{\partial t} = \operatorname{div}\left(\frac{\nabla u}{|\nabla u|}\right) + \lambda\left(u_0 - u + v\right)$$
$$\frac{\partial v}{\partial t} = \alpha\left(u_0 - u\right)$$

- ∇_σ Gradient smoothed by a Gaussian
- λ Controls the strength of the filter
- α Regularization parameter (quality refinement)
- N Number of iterations
- $\tau = \partial t$ Time increment

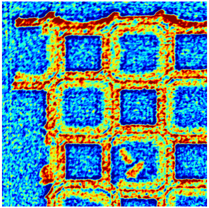
Comparing different filters

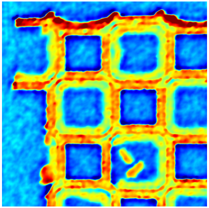


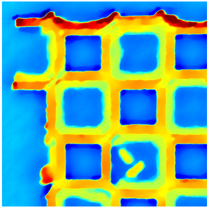
Kaestner et al. [2008]

An example with the ISS filter

Neutron CT of a diesel particulate filter


Original


100 iterations


1000 iterations

Filter time for 1.5 Giga voxels 34h...

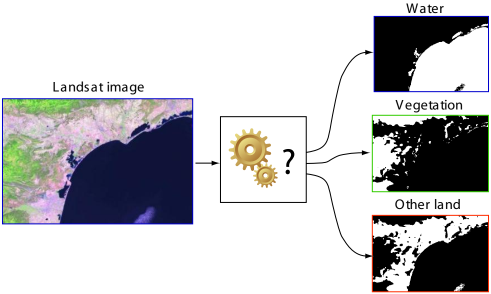
Gruenzweig et al. [2012],Kaestner et al. [2012]

Segmentation

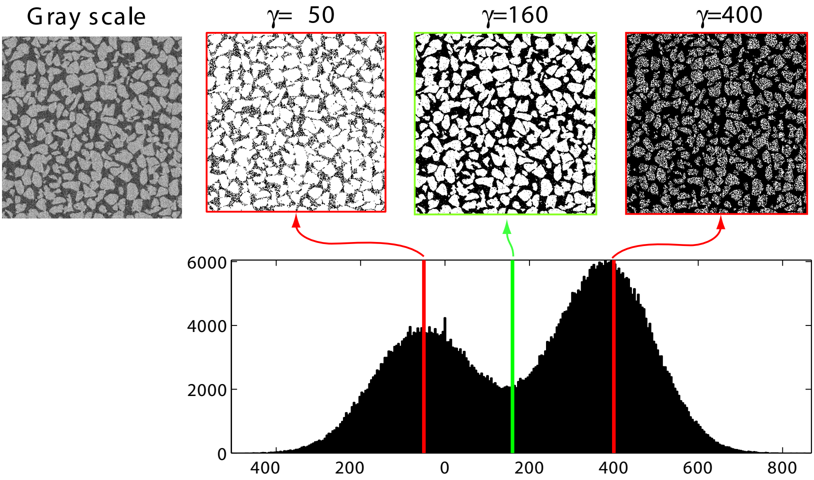
What is segmentation?

Segmentation is the process to convert the pixels in an image into a limited (small) number of classes depending on:

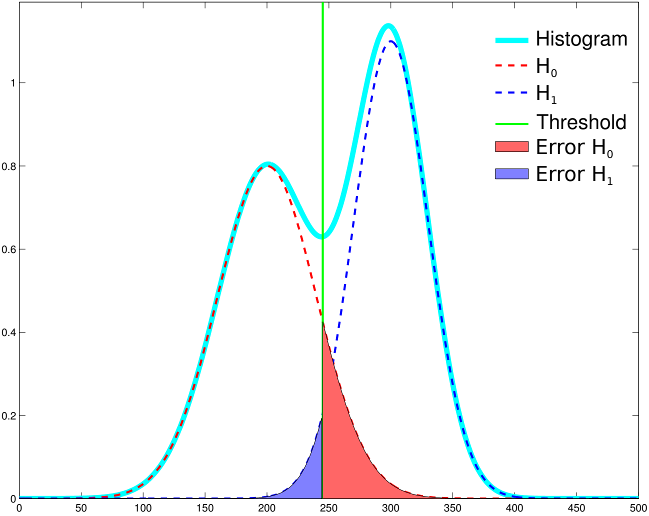
- The histogram of the image
- A-priori knowledge of the statistics in the image
- Neighbourhood information



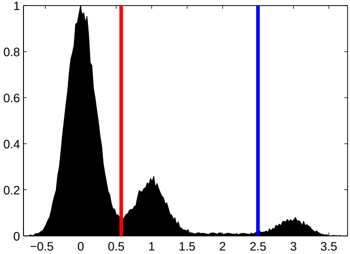
Manual thresholding

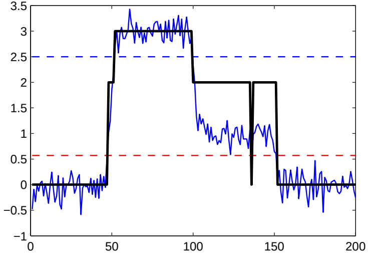


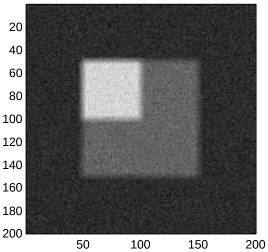
Detection performance

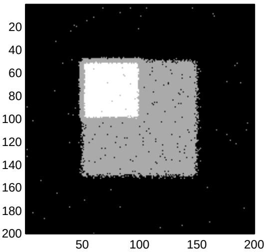


Multi-class classification







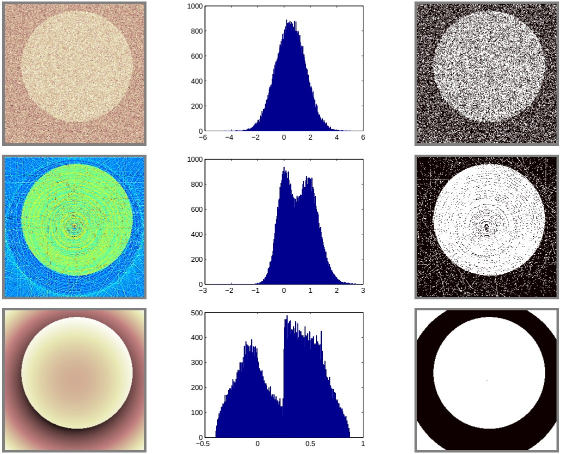


Problematic cases

Low SNR

Artifacts

Gradients



Proper preprocessing can reduce these effects

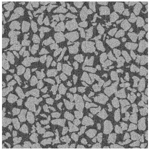
Histogram based classification

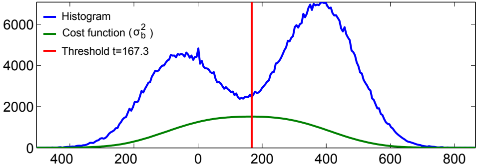
A classic algorithm to find the threshold of an image Otsu [1979].

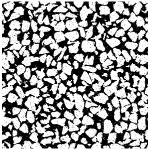
Find a threshold that

- Minimizes the in-class variance
- Maximizes the between-class variance

using the histogram of the image.





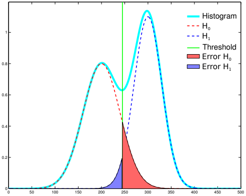


Threshold with hysteresis

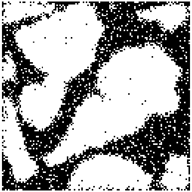
To improve the classification performance with overlapping histograms

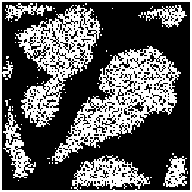
A single threshold would either be

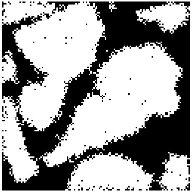
- too low $\rightarrow$ undesired pixels are assigned
- too large, only desired pixels are assigned.




Input f


$f > a$


$f > b$


Growing $b \rightarrow a$

Further classification methods

Depending on your task, basic thresholding is not sufficient:

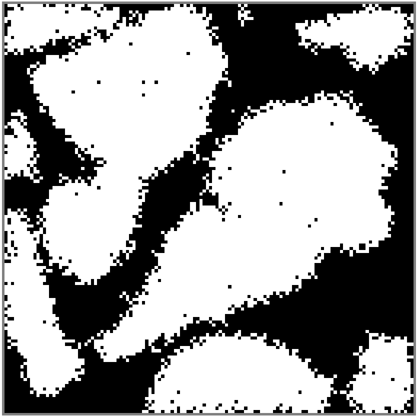
- Fuzzy C Means
- Region growing/tracking
- Scale pyramids
- Active contours
- etc...

Some concluding words

- No sample or sample condition is like the other
  $\rightarrow$ Classification method must be chosen with care every time
- Clean images are easier to work with
  $\rightarrow$ Put some extra time in enhancement.
- Interactive classification can improve the performance
- Classification and pattern recognition is an active field of research

Clean-up

The classification is not 100% perfect



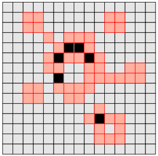
Something is needed to clean up misclassified pixels

Morphological operations

Morphological operators act as search and replace operation.

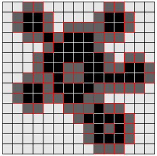
Some structure elements

Erosion



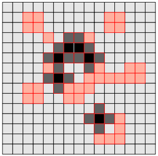
Region shrinking

Dilation



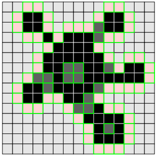
Region growing

Open



Erosion $\rightarrow$ Dilation

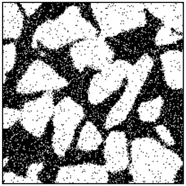
Close

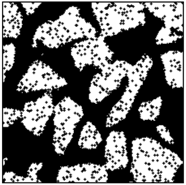


Dilation $\rightarrow$ Erosion

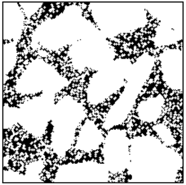
Testing morphological operators with $SE =$

Input

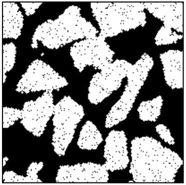




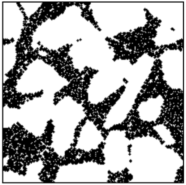
Erosion



Dilation



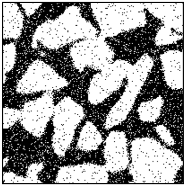
Open

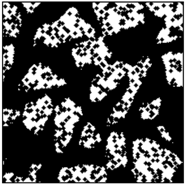


Close

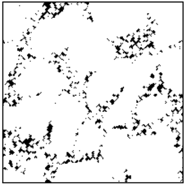
Testing morphological operators with $SE =$

Input

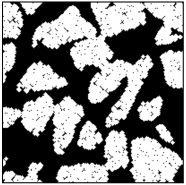




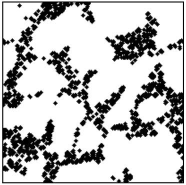
Erosion



Dilation



Open



Close

What's next?

Finalizing the analysis

The previous steps

- Information enhancement, denoising etc.
- Classification
- Cleaning

are more or less similar.

The next steps

Depend on the purpose of the experiment:

Exploration/Visualization What are the contents of the sample.

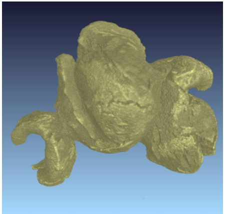
Quantification Sample composition and dimensional analysis.

Verification of model describing the observed process.

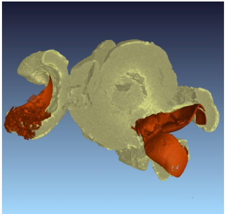
Fault detection Identify and measure dimensions of faults.

Data visualization

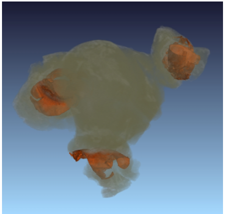
Basic methods



Iso-surface



Volume cutting

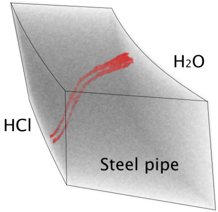


Volume rendering

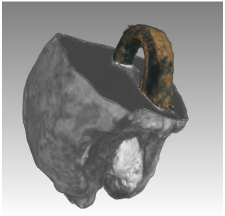
Reasons to visualize the data

- Explore the data
- Qualitative data understanding
- Publications

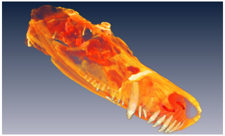
Some visualization examples



Fault inspection



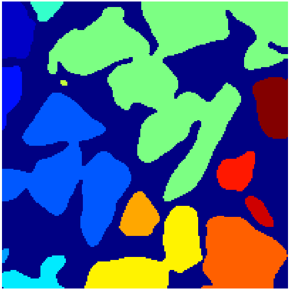
Material composition



Anatomy

Structure analysis – Labelling

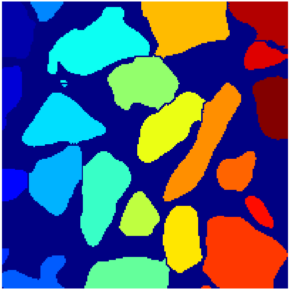
Connected components



- Touching grains
  → single item.

\+ No preprocessing

Watershed



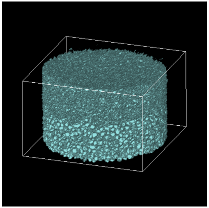
- Over-segmentation
  → Pre-processing

\+ Identifies touching grains

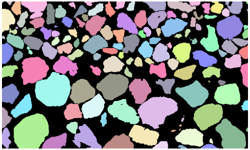
Soille [2002]

Example with watershed segmentation

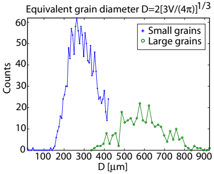
Sample

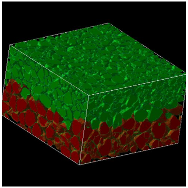


Processing

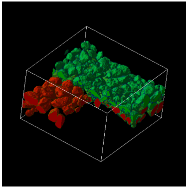


⇒





All grains

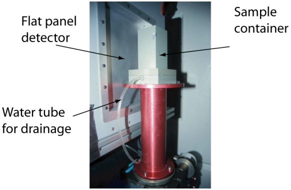


The interface

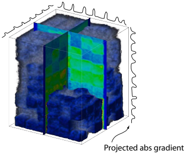
Kaestner et al. [2005]

Estimate water content over time

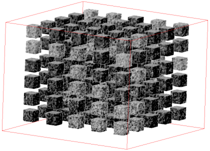
On-the-fly CT



Find regions

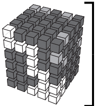


$\Rightarrow$

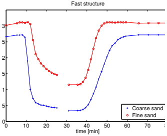


Estimation

$$\theta_C(t) = E\left[f(p,t)|M(p) = C, M \in \right.$$



$$\left.\right] \Rightarrow$$

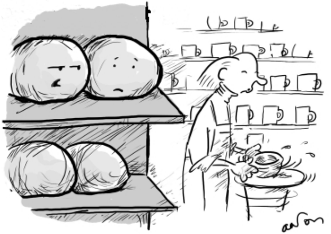


Kaestner et al. [2007]

Verify the correctness of the method

Data massage

- Operations manipulate the data
  → avoid strong modifications.
- Too much a priori
  → expected but wrong results.
- Interactive processing is subjective.



Watch that man, he'll make mugs of us all!

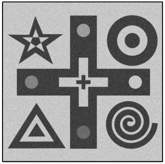
Verify the validity your method

- Visual inspection – does the result make sense
- Difference images – Detect finer changes
- Use degraded phantom images – Thorough statistic evaluation

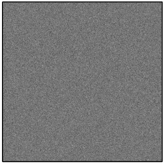
Visual verification

Inspect: *Error = Original − Processed*

Noisy image

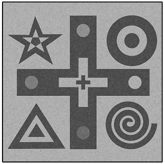


Ideal filter

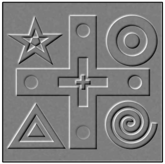


Over smoothing

Intensity scaling



Geometric shift



Summary

Summary

Image processing. . .

. . . is a collection of computational methods to analyse images.

. . . often requires a sequence of operations.

. . . can improve the image quality.

. . . should be used with care.

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