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Characterization of cracks in cement-based materials by microscopy and image analysis

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Outline

Materials Science & Technology

- The problem:

characterizing the damage produced by the Alkali-Aggregate Reaction

- Types of microscopy
- Crack segmentation by clustering
- A few conclusions
- Suggested bibliography

Foreword

- All the image processing and analysis presented herein was done with **Fiji**

- **Fiji** is a version of **ImageJ** with lots of additional plugins already pre-installed

  http://fiji.sc/wiki/index.php/Main_Page

- **ImageJ** is a software suite for image processing and analysis written in Java

  - developed and maintained at the National Institutes of Health (NIH), USA

  - a standard in the biomedical sciences

  - lots of plugins contributed by researchers and developers around the world

  http://imagej.nih.gov/ij/

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Characterizing the damage produced by the Alkali-Aggregate Reaction

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- cement-based materials (mortars, concrete, cement-based composites)

Characterizing the damage produced by the Alkali-Aggregate Reaction

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- Alkali-Aggregate Reaction (AAR):

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Characterizing the damage produced by the Alkali-Aggregate Reaction

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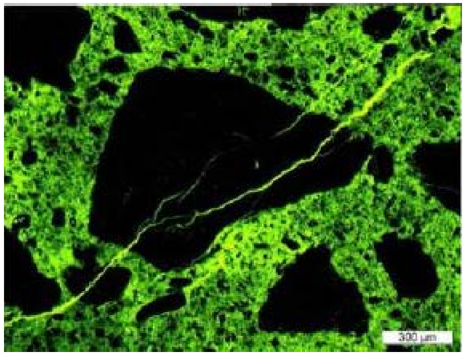
- Alkali-Aggregate Reaction (AAR):
  - set of intrinsic chemical reactions between the alkali of the pore solution and the aggregates
  - hygroscopic amorphous reaction products $\Rightarrow$ expansion $\Rightarrow$ cracking



optical micrograph, obtained with UV-light, of a polished cross section from a concrete sample affected by the AAR. The sample was impregnated with a resin doped with a fluorescent dye. Courtesy of A. Leemann.

Characterizing the damage produced by the Alkali-Aggregate Reaction

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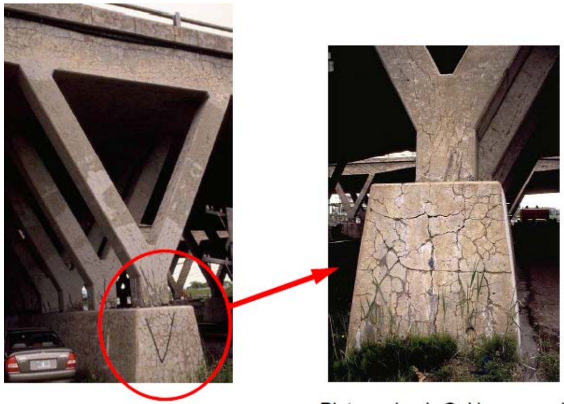
- Alkali-Aggregate Reaction (AAR):
  - ➢ set of intrinsic chemical reactions between the alkali of the pore solution and the aggregates
  - ➢ hygroscopic amorphous reaction products ⇒ expansion ⇒ cracking
  - ➢ particularly severe with silica-rich aggregates
  - ➢ kinetics on the scale of years/decades ⇒ slow degradation of concrete infrastructure, especially old ones



Pictures by J.-G. Hammerschlag

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- Microscopy and quantitative image analysis of cracking
  - ➢ how does the porosity evolve in time due to cracking ? $\Rightarrow$ crack segmentation

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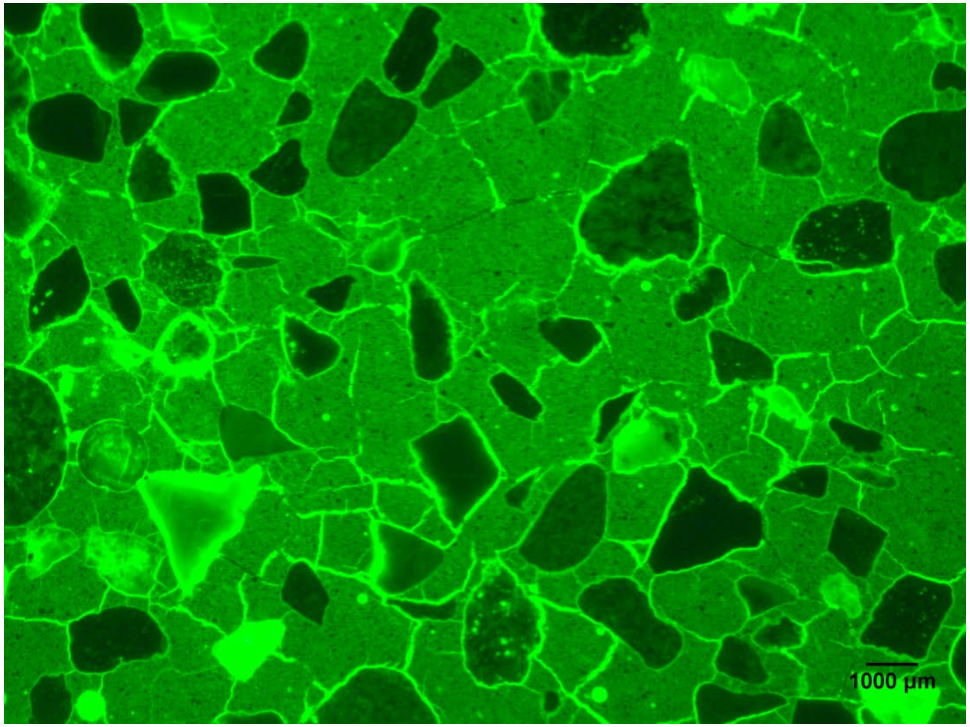
Types of used microscopies:
UV-based optical microscopy of cross-sections

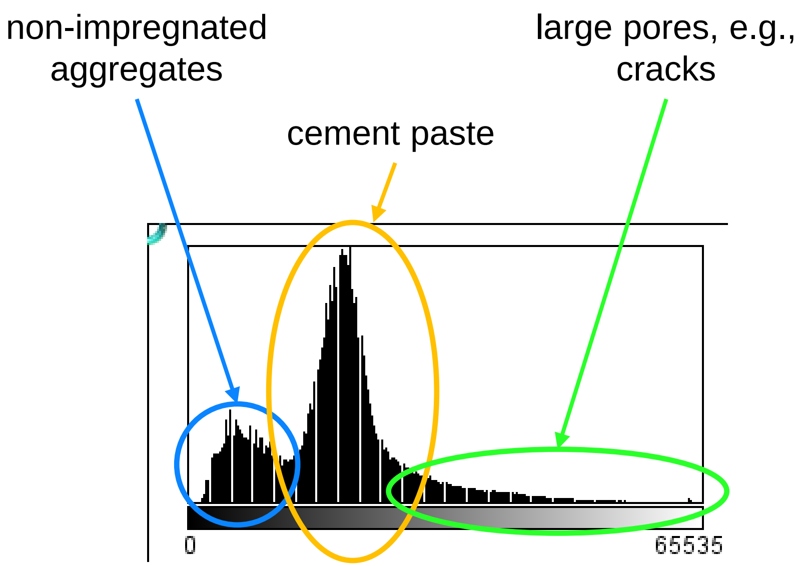
- impregnation under vacuum with a resin ⇒ fix the microstructure
- the resin is doped with a fluorescent dye
- optical microscopy using UV lamp as illuminating source
- larger porous regions ⇒ higher resin density ⇒ higher pixel value in the image



Mortar sample subjected to a thermal conditioning at 650°C for 3 hours.

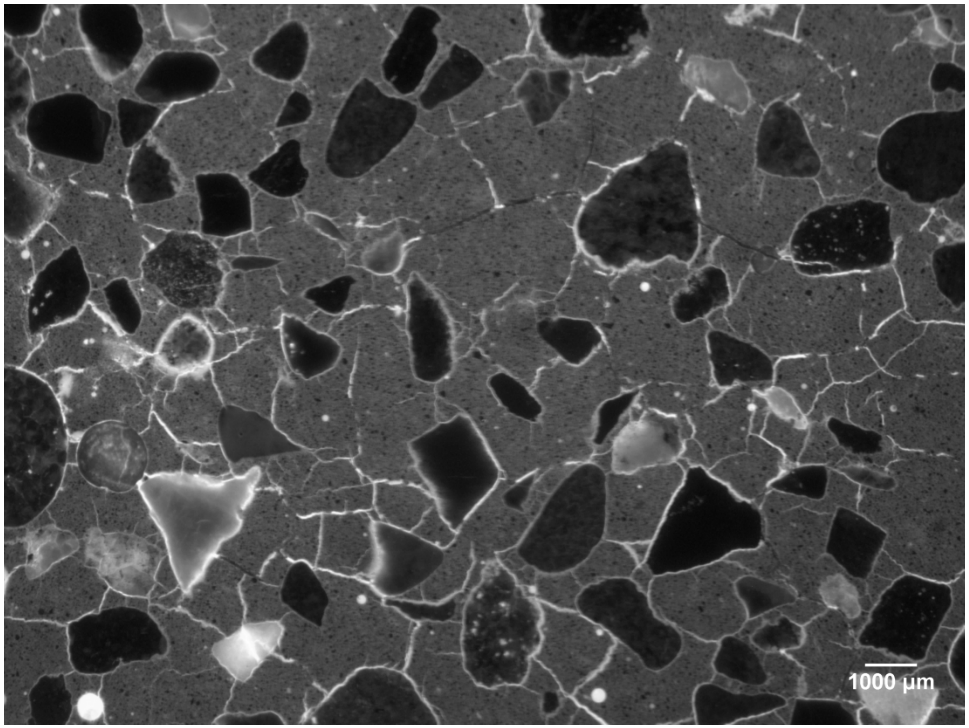
Types of used microscopies: UV-based optical microscopy of cross-sections

- different material phases/features have different ranges of pixel values
- segmentation by thresholding (see talk of Hannelore Derluyn)



Pixel value histogram for the 16-bit grey image

16-bit grey image obtained by conversion from the original RGB image

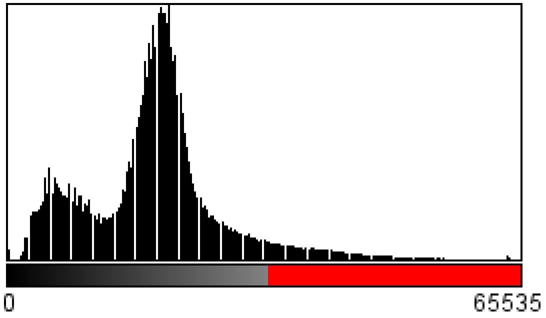


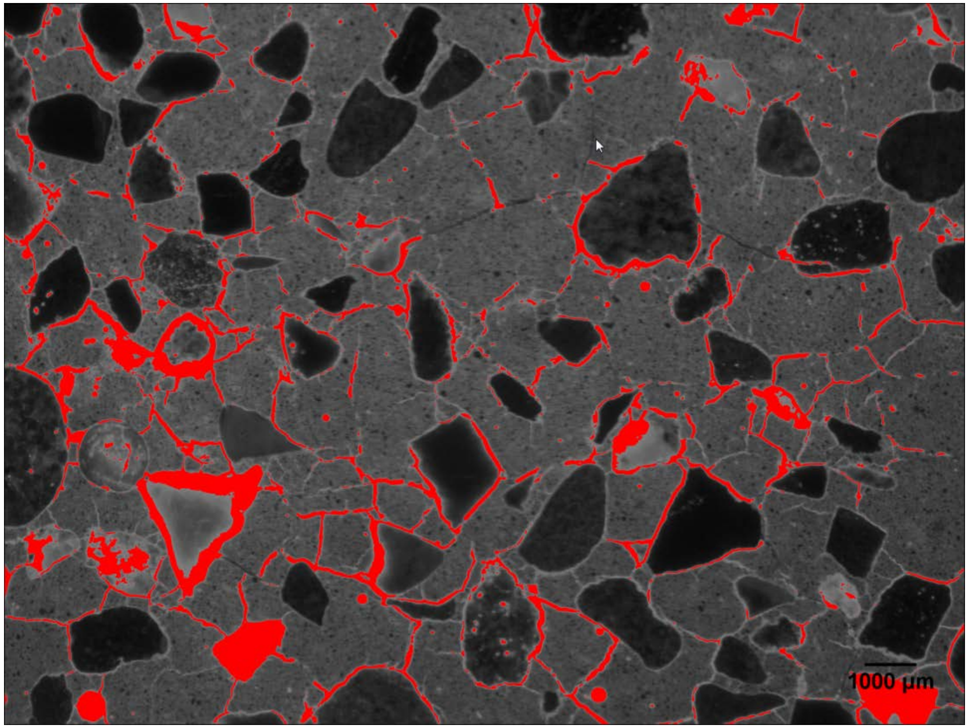
Types of used microscopies:
UV-based optical microscopy of cross-sections

- example of automatic choice of the threshold (pixels with value above the threshold are colored as red)

- **global** threshold chosen by the a method based upon the **maximization of the a-posteriori entropy of the pixel value histogram***

* J.N. Kapur *et al.*, Comp. Vis. Graph. Image Proc. 29, 273 – 285 (1985)





Types of used microscopies:
X-ray Tomographic Microscopy

- completely non-destructive
- 3D information

Single cross-sectional CT slice (image)

Synchrotron radiation-based
X-ray Tomographic Microscopy.

Edge-enhancement mode ($D_{S\text{-}D}$ = 40 mm)

Wide Field-Of-View configuration
(4020 x 4020 pixels)

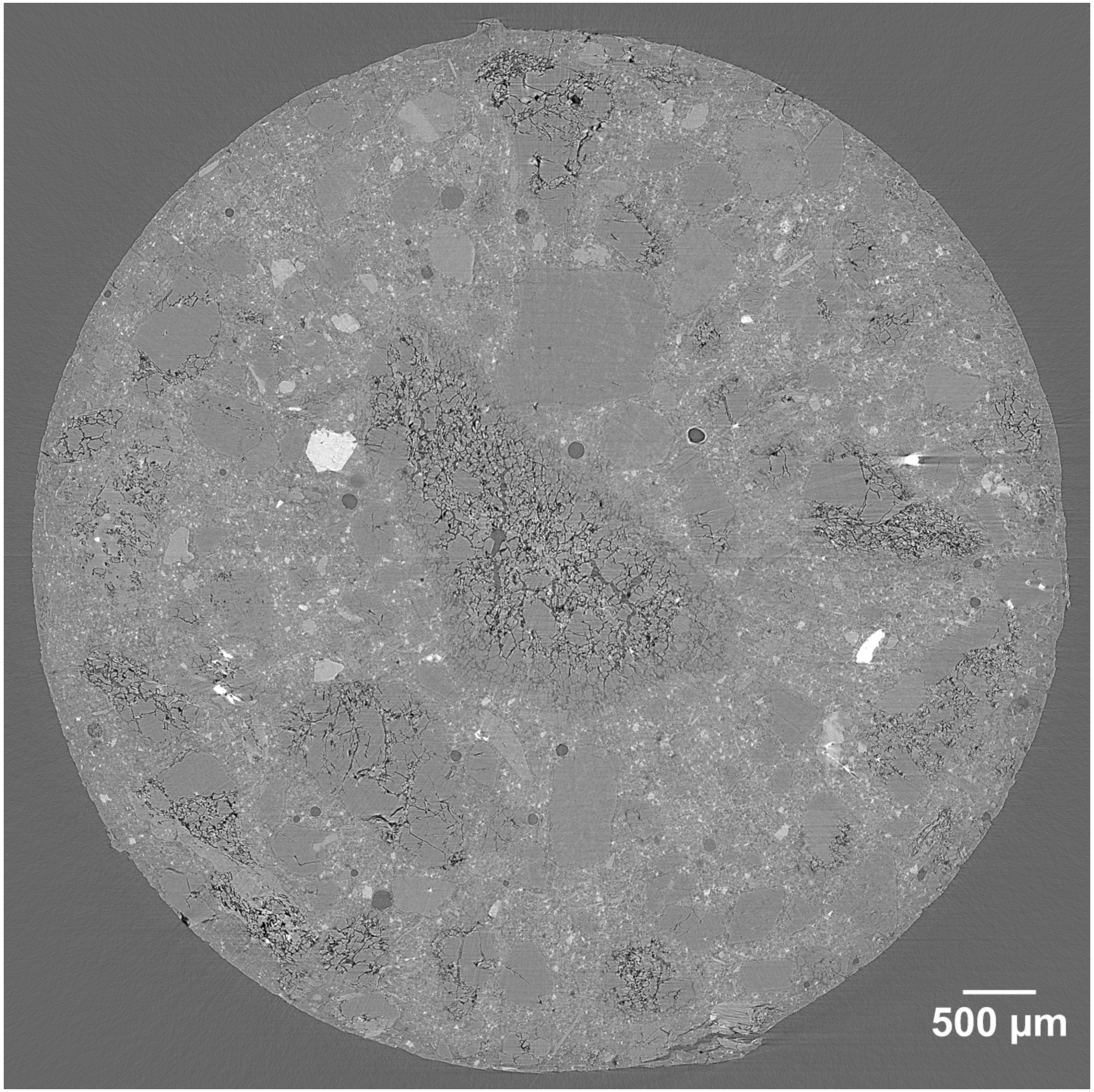
Voxel lateral size = 1.85 μm.

Measurements at the TOMCAT beamline,
SLS, PSI.

Cylindrical mortar sample, 7 mm ø

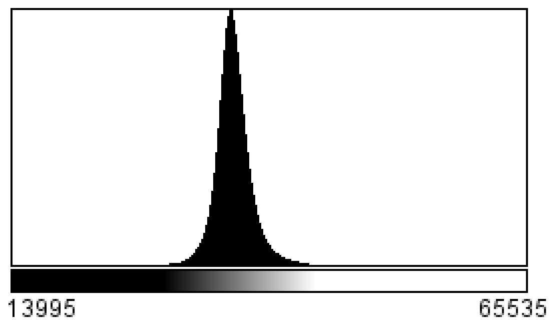
Highly reactive aggregates.

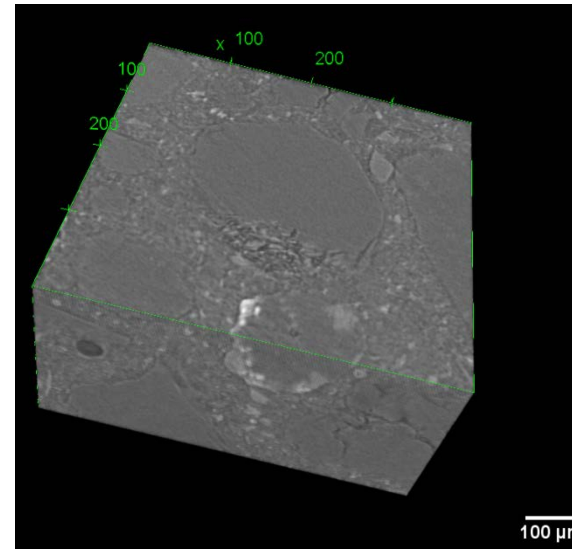
AAR acceleration protocol followed for 8 weeks



Types of used microscopies:
X-ray Tomographic Microscopy

- focus on a smaller ROI, 400 x 400 x 201 voxels
- unimodal voxel value histogram, difficult to define a threshold level





- complicated pore system: cracks + aggregate dissolution pores

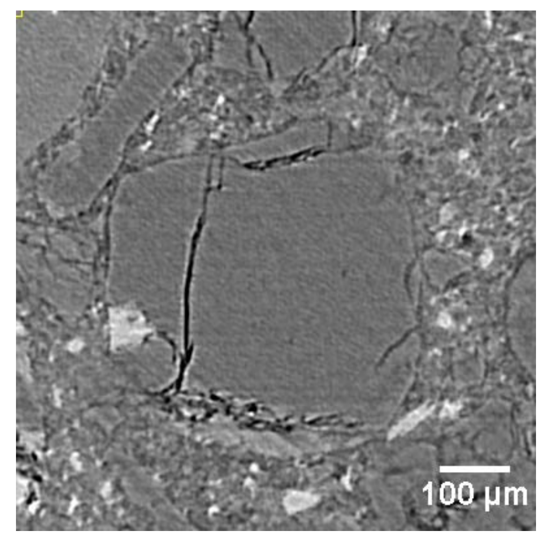


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Image segmentation by clustering

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- data clustering for pattern recognition, machine learning, data compression and data mining

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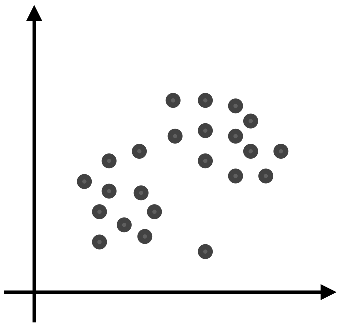
- dataset = set of points $\vec{x}_i, i = 1, \dots, M$, in a Euclidean vector space R^n (the feature space)



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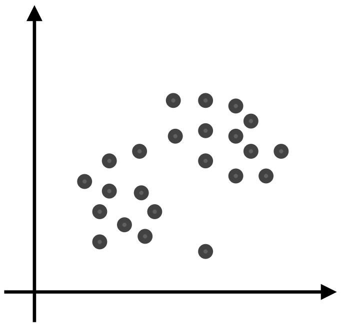
  - image as an ensamble of *M* points $\vec{x}_i$ (pixels or voxels), where *n* = 1 (grey value image) or *n* = 3 (RGB image) or whatever (not only the pixel/voxel value as feature)



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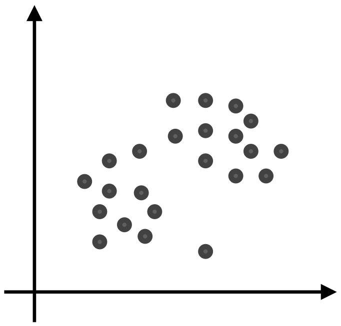

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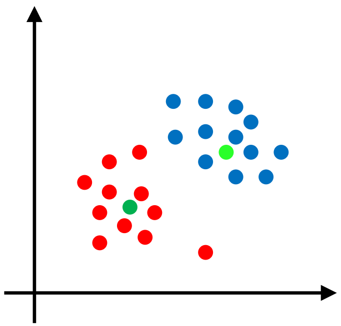

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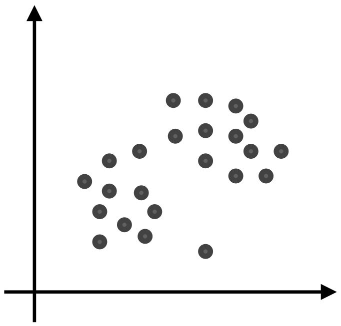

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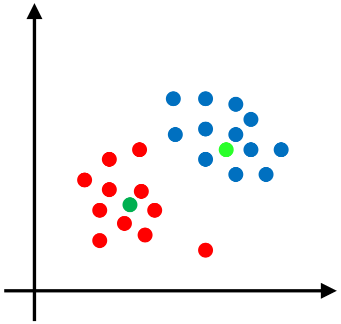

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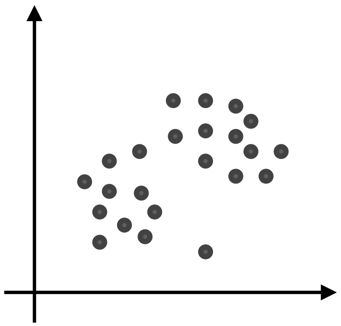

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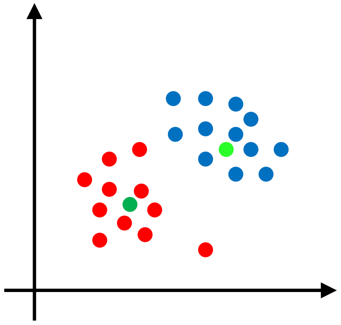
  - starting from initial guesses, iteratively find *K* reference points $\vec{y}_l, l = 1, \ldots K$, and corresponding clusters, that decrease a global (i.e., for all the clusters) distance metric function till finding its minimum



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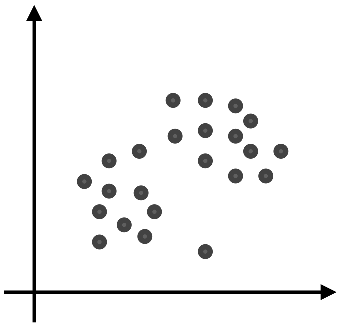

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  - segmented image ⇔ pixel/voxels belonging to the *l*-th cluster are assigned the value of the respective *l*-th reference point

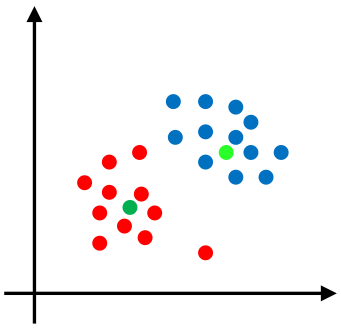

Image segmentation by *K*-means clustering

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- ***K*-means clustering**: a class of data clustering algorithms

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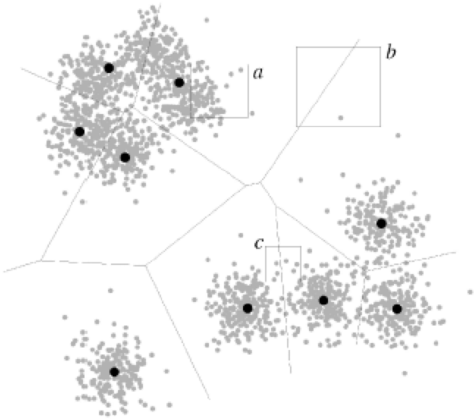
- ***K*-means clustering**: a class of data clustering algorithms

(1) at each iteration, create the clusters by the **Voronoi partitioning** of the feature space based upon the current reference points



Adapted from Fig. 3 of T. Kanungo et al., IEEE Trans. Patt. Anal. Mach. Intell. 24 (7), 881 – 892 (2002)

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- ***K*-means clustering**: a class of data clustering algorithms

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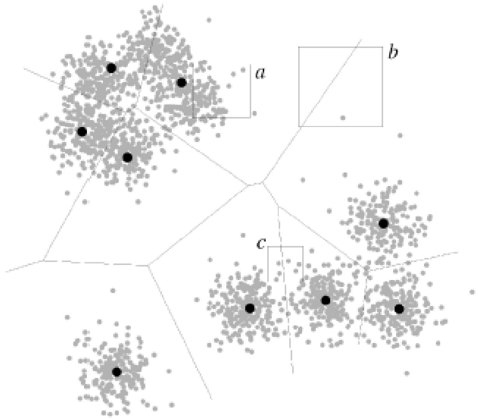
(2) for each cluster, calculate the **centroid** (mean/average value)



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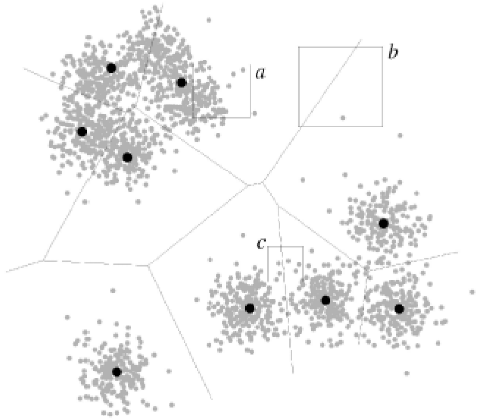

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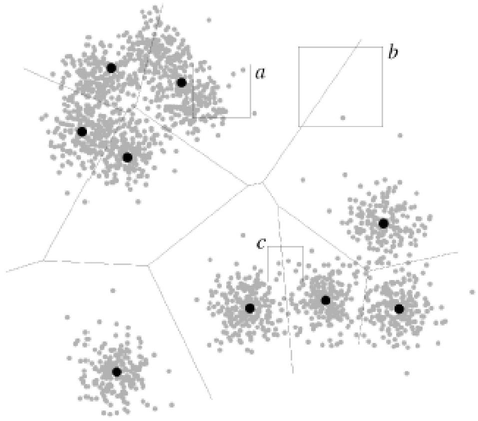

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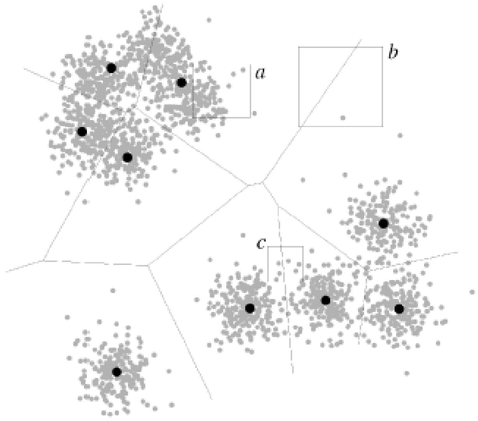

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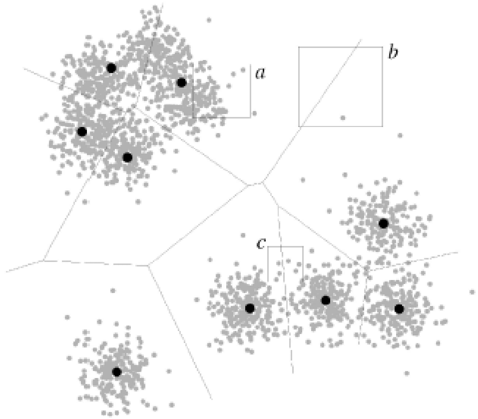

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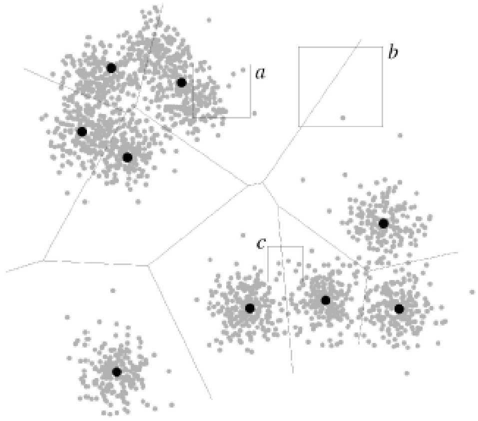

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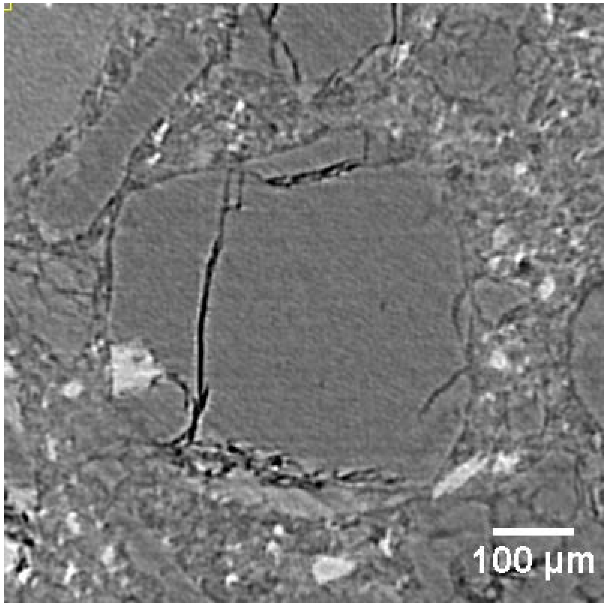
  - ➢ different algorithms have different computational efficiency and overload
  - ➢ belong to the class of **Centroidal Voronoi Tessellations** algorithms
  - ➢ no parameters involved, except for *K* (number of clusters) and total number of iterations

Crack segmentation by *2*-means clustering

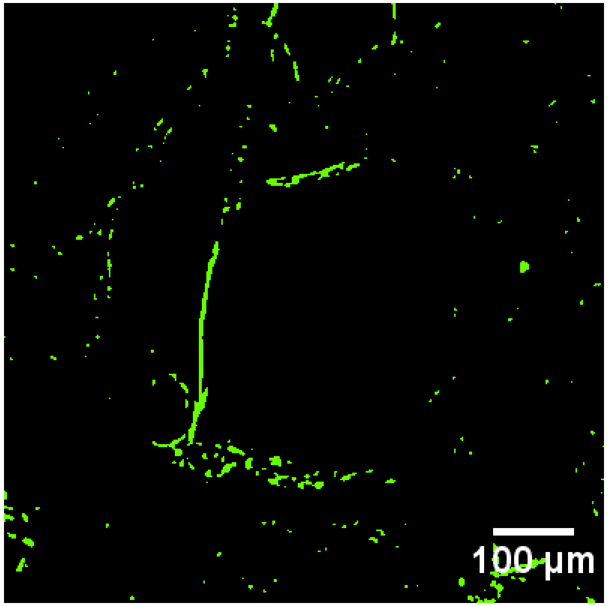
- assumed K=2 clusters (pores and solid phases)
- *2*-means clustering of the entire 3D ROI (volume)
- feature space dimensionality n = 1 (only voxel grey values used)

filtered, original ROI



slice # 98 of 201

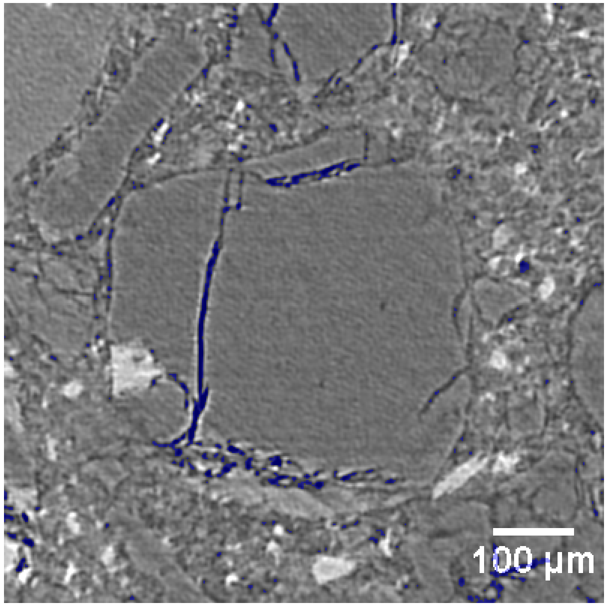
after 2-means clustering (binary image)



slice # 98 of 201

green = pore space voxels
black = solid phase voxels

overlay of the binary image on top of the original



slice # 98 of 201

blue = voxels classified as belonging to the pore space

Crack segmentation by *2*-means clustering

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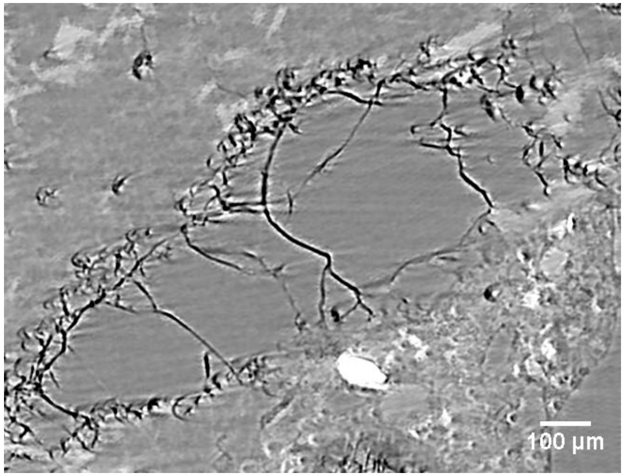
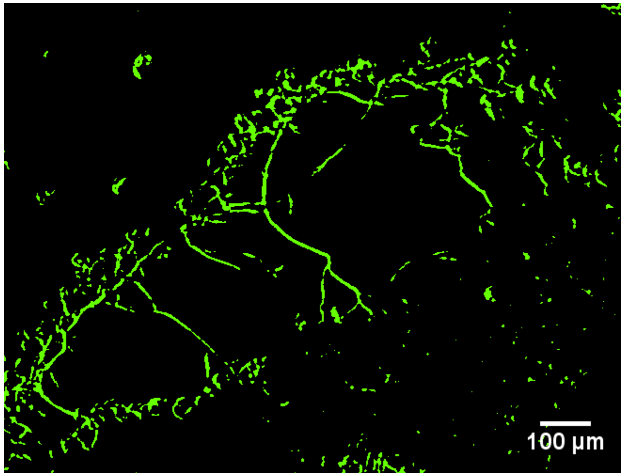
- another 3D ROI, 656 x 500 x 400 voxels
- same processing as for the previous ROI

filtered, original ROI



slice # 179 of 400

after 2-means clustering (binary image)



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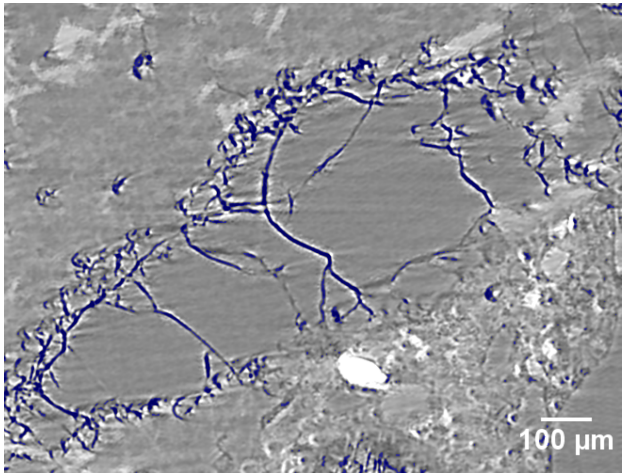

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A few conclusions

- segmentation by 2-means clustering worked very well on my 3D images
  - not perfect, but much more efficient than other algorithms, e.g., manual thresholding
  - it may not work as well on your images: the best segmentation algorithm type is image-dependent !

- I have segmented solid phases and pores: how about cracks only ?
  - use morphological operators for ``closing´´ small, spherical-like pores with volume smaller than a certain threshold

- only 1D feature space for the data clustering !

  Better results achievable by choosing additional feature variables for the pore space voxels, e.g., spatial coordinates and/or local morphological properties of the image itself

Suggested bibliography

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Data clustering and image segmentation

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