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Image segmentation of x-ray microtomography of highly porous media - a work in progress

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Summary

In this work we consider two learning based methods, to segment void and pore structures of x-ray μCT volumetric data of porous chalk rocks. The methods utilize synthetically generated datasets as ground truth in the training phase and as accuracy estimation.

Our problem

It is impractical and inaccurate to determine the feasibility of segmentation methods by visual inspection alone, due to the resolution and level of complexity of datasets. For those reasons, annotated data is not readily available. Consequently, dataset specific regularization parameters are difficult to justify in any energy formulation of the problem. Particularly in the case of our data, there is a clear trade off in computation time and accuracy. The latter which is an essential, as the segmentation serves as a stepping stone in a larger analysis pipeline.

A XY-slice of the actual datasets we are working on (left) and our currently best segmentation estimate (right) can be seen below. Here one voxel (volume pixel) corresponds to 50 nm. One dataset is ~4 GB.

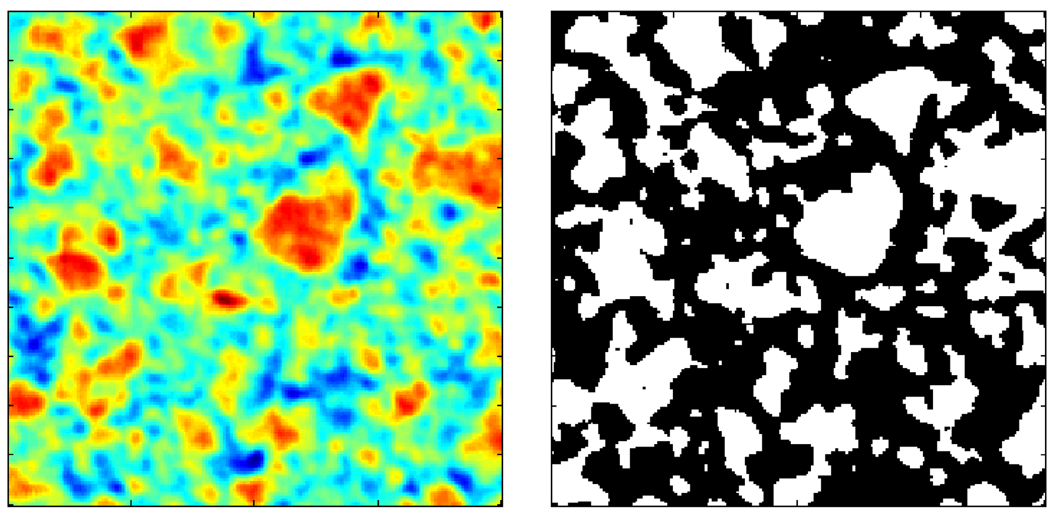


Figure 1: Experimental dataset (left) shown in color to highlight complexity and the current best segmentation (right), with our active countour based method, using Chambolle-Kremers-Pock regularization of the length term

Our approach

In order to get access to ground truth data for training the methods and compute measures of accuracy, we synthetically generate data that mimics the statistical behaviour of experimental datasets. To be able to approximate experimental datasets as closely as possible, we add blurring, noise, ringing, and bias field artefacts, as well as a diagenetic models as a post processing step.

We consider two novel learning methods for segmenting the data; (1) a trained optimized reaction diffusion process, proposed by Chen, Yu, and Pock; and (2) reformulating Jose Caballero's work on a spasely encoded dictionary based learning method for joint reconstruction and segmentation of MRI imaging to fit our X-ray μCT problem.

Synthetic data generation

- Multiphase segment data volume
- Compute watershed regions for each label, using distance maps and minima imposition
- Transform regions to diameters of spheres that share the same volume, sort them, and compute the cumulative sum to sample from.
- compute distribution of different labels to sample a rock type from

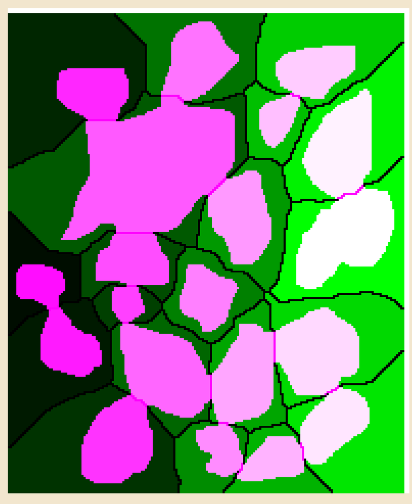


Figure 2: Watershed ridge lines, superimposed on an example dataset.

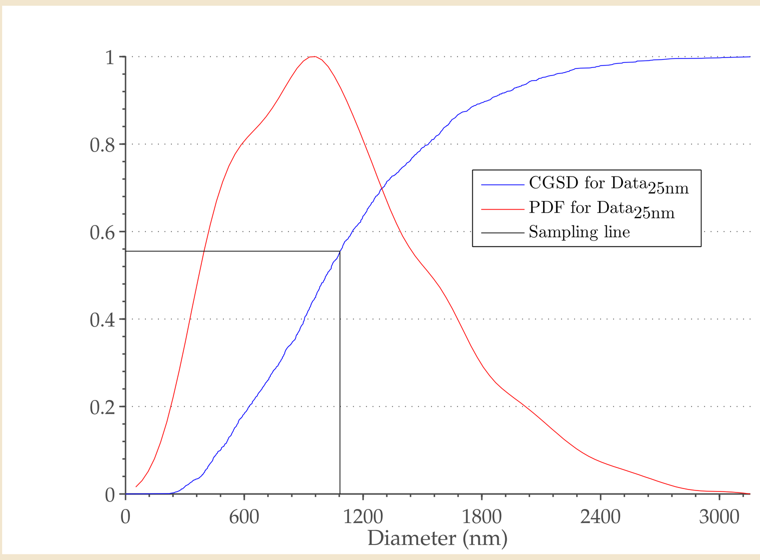


Figure 3: Inverse transform sampling of the generated grain size distribution.

Simulating multiphase grains and artefacts

- A material is sampled from the distribution of labels
- Sampled radii are converted to randomly shaped convex grains, and rescaled to fit the corresponding volume.
- Grains are initialized in a grid like towering structure before they are simulated, using Kenny Erleben and Sarah Niebe's PROX simulator.

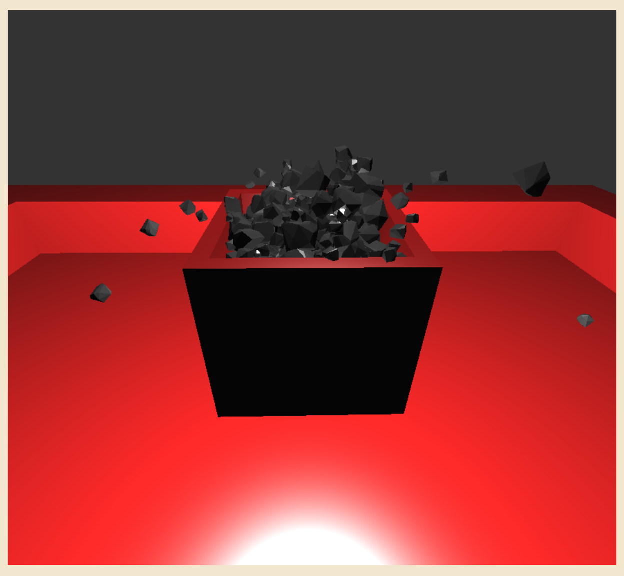


Figure 4: End of running the PROX physics simulation; all contact forces are at an equilibrium, so no changes occur - grains are collected in the container box or the larger collection box below.

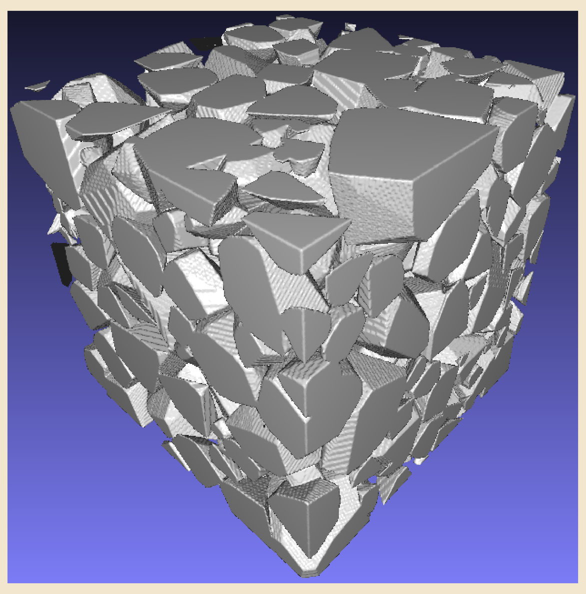


Figure 5: The meshed solid space of the generated dataset, here a single phase is shown representing all solids.

- Simulated grains are converted back into a volume mask of labeled grains.
- The mask is saved and used as ground truth for comparison and calculation of similarity measures.
- Artefacts like ringing effects, intensity inhomogeneities, and noise distribution models are added to the generated data and can now subsequently be used for training and testing of methods.

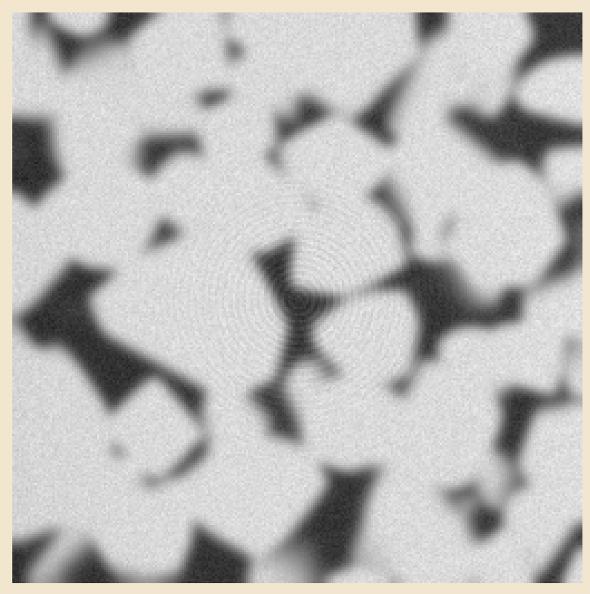
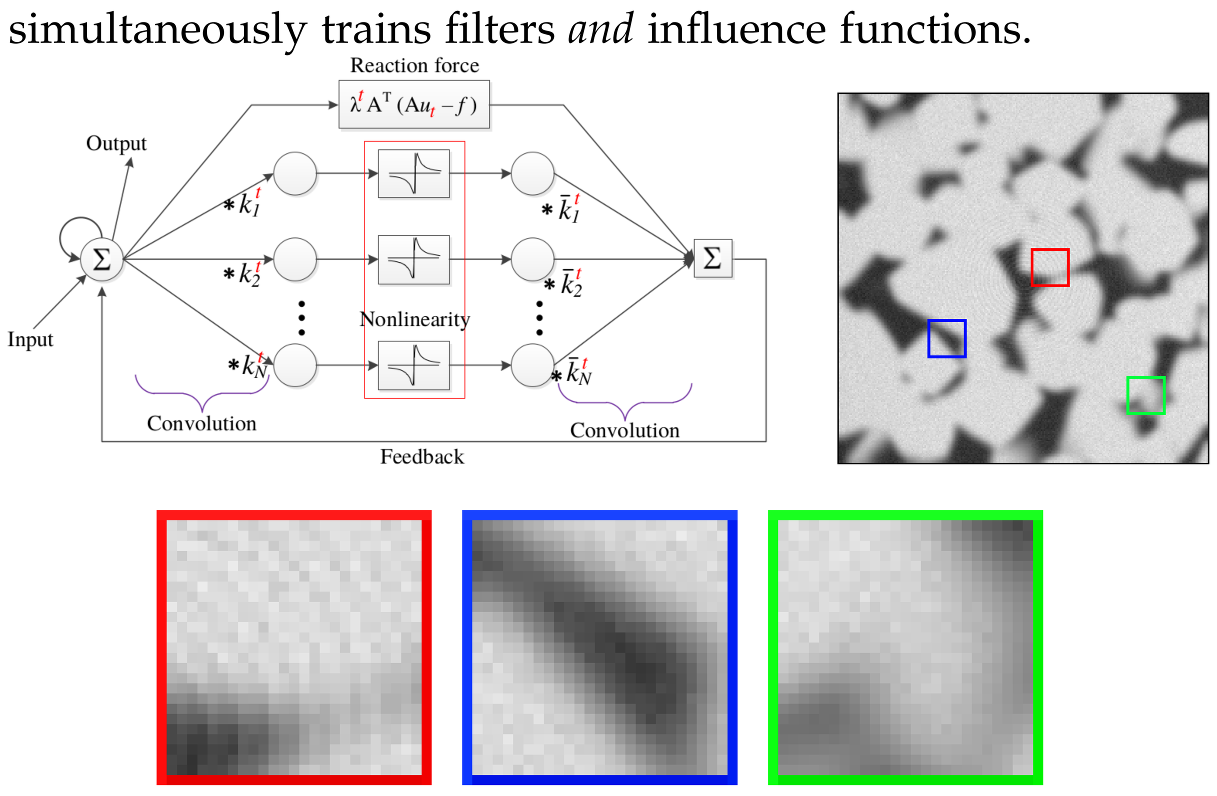


Figure 6: Slice of synthetically generated dataset, after having applied artefacts and noise models.

Learning optimized reaction diffusion processes

Based on the recent paper "On learning optimized reaction diffusion processes for image restoration", by Chen, Yu, and Pock. Based on the Perona-Malik diffusion model, but simultaneously trains filters *and* influence functions.



Dictionary based learning for joint reconstruction and segmentation

- patch-based dictionary sparse coding, with the following energy formulation, from the Ph.D. Thesis of Jose Cabellero:

$$\min_{\Gamma,\theta,x} ||F_u x - y||_2^2 + \frac{\lambda}{N_p}\sum_{n=1}^{N} ||R_n x - D\gamma_n||_2^2 - \beta \ln p(x \mid \theta) \quad \text{s.t.} \quad ||\gamma_n||_0 \le s, \ \forall n$$

Here $\mathbf{x}$ is the data we wish to segment, $\mathbf{D}$ is the patch based dictionary, $x_u = F_u x$ is undersampled collected data.

The problem formulated above is non-convex, but by updating the optimization variables independently, the solution can be approximated. Therefore, albeit we are not guarenteed that it will converge, we have saparated the global problem to three local ones, that either are convex or can be sufficiently solved by a greedy method. The idea is to alter the second term and potentially add more fitting regularization terms to our dataset. The third term is a GMM term.