HIGH-RESOLUTION 3D IMAGE ANALYSIS OF SATURATED PORE SPACE: HOW IMAGE SEGMENTATION AND MACHINE LEARNING CAN BE APPLIED TO GROUNDWATER REMEDIATION

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Groundwater reservoirs are distinguished by the petrophysical characteristics that condition their capacity to store (i.e. reservoir porosity) and transmit (i.e. reservoir permeability) significant volumes of groundwater that can be exploited by society (Feitosa *et al.*, 2008). Recent works (Archilha, N. L., 2015a; Archilla *et al.*, 2016; Eberli *et al.*, 2003) showed that specific properties from the pore space, such as pore geometry and pore connectivity, also control the pore space permeability. High resolution X-ray imaging can reveal complex 3D structures without destroying the samples. Through digital slicing, it is possible to determine pore surface area, volume, connectivity, and many other microproperties of individual pores. In the case of saturated pores spaces, it is also possible to reveal and distinguish the different saturating phases, such as oil, contaminants, water, gas, etc. All this characterization is only possible if the 3D image, originally in grey scale, is segmented, i.e. partitioned into multiple segments that share the same attributes. In this work we segment two saturated pore scales: (i) a real dolomite rock, saturated with a non-aqueous phase liquid (NAPLs) and water and (ii) a pack of glass beads saturated with water and a toxic halocarbon industrial solvent. The segmented image is now being used to train different machine learning models for, soon in the future, turn this time-consuming segmentation method into a quick and reliable process. This has a very important implication to a cutting-edge technique: time resolved X-ray tomography (so called 4D X-ray tomography), which allows the 3D study, in real time, of any type of fluid flow in porous media.

SCIENTIFIC MOTIVATION

The process of cleaning the subsurface groundwater resources contaminated with nonaqueous phase liquids (NAPLs) and chlorinated solvents have been the subject of extensive research in the recent decades and new technologies are always in demand. Water injection is a well-known technique used to remove these contaminants; however, it is also known that displacement of a non-wetting phase by a wetting phase is not 100% efficient and a portion of the contaminant will remain within the pore space. New technologies, such as nanoremediation, are showing great potential for increasing the remobilization of contaminants or even degrading them in-situ. Regardless of how groundwater remediation will be conducted, the pore scale visualization of the displacement process is fundamental to help understand and improve the remediation technology. This is only possible through a cutting-edge technique: the high-resolution X-ray tomography. This technique allows the internal investigation of a sample without destroying it and, depending on the image resolution, it is also possible to resolve the pore space, identify and quantify different saturating liquids within them.

SAMPLES AND EXPERIMENTAL METHODOLOGY

In this work, X-ray tomography was used to study two different types of samples: (i) a real carbonate rock and (ii) a pack of glass beads, which is normally used to model soil and rock pore spaces. X-ray tomography is a transmission technique, which involves the rotation of a sample in front of an X-ray beamline while the detector collects more than 1000 projections (radiographs) over 180º. A scintillator positioned between the sample and the detector transforms X-rays into visible light and an objective is responsible to magnify the image. Thereafter, reconstruction algorithms are used to generate a 3D image of the sample from the radiographic images. The voxel size, for the two cases shown in this work are 13 and 3.2 micrometers, respectively, for the carbonate rock and glass beads.

MANUAL AND SEMI-AUTOMATIC SEGMENTATION METHODOLOGY

The objective of the image segmentation is to separate and individualize different structures/fluid phases of the sample. This way, it is possible to evaluate, for example, porosity and fluid saturation. For this purpose, *Avizo* and *Fiji (ImageJ)* were used for image filtering and segmentation.

The first part of the analysis includes filtering the image using *Avizo* with the aim of improving the quality of the images, mainly reducing noise and image artifacts. In this process, two digital filters were necessary: (i) *Non-Local Means* (NLM), which takes a mean of many pixels of the image, weighted by how similar these pixels are from the target pixel; and (ii) *Unsharp Masking* (UM), which is an image sharpening technique, which enhances the edge regions. Then, the filtered data is first segmented in *Avizo*. The process consists on using the *Threshold* tool in order to separate the image into different categories (e. g. background, matrix, pore and contaminant) according to the gray level histogram. Some ranges of gray levels are hard to define as belonging to a particular group and, for those cases, *Watershed* segmentation tool is used. It is based, first, on the identification of seeds/markers. Then, these regions start to grow until it reaches a barrier in terms of gray levels (the barrier is easily determined by a gradient image), facilitating the determination of distinct regions. The described methodology usually does not provide a perfect segmentation, making manual corrections necessary, which were made with *Brush*, *Magic Wand* and *Lasso* tools.

Since this processing is time-consuming, the *ImageJ* was also used. The tool is *Trainable Weka Segmentation* (TWS), distributed as open-source software as part of the *Fiji* image processing distribution of *ImageJ*. The TWS is a machine learning tool that trains a classifier from manual annotations, making possible an automatically segmentation. In general terms, it was observed that *Avizo* presented better results in segmentation of small regions (few voxels) and *ImageJ*, for big regions.

RESULTS AND DISCUSSION

In this section we present the results of the segmentation of two samples. In Figure 1, a raw (left) image of a 4-mm diameter sample of glass beads is segmented (right) into three phases: background (black), beads (light blue) and pore space (dark blue). For 1000 slices of this image, specifically, the segmentation process took about 2-3 hours, but manual corrections can increase this time to tens of hours.

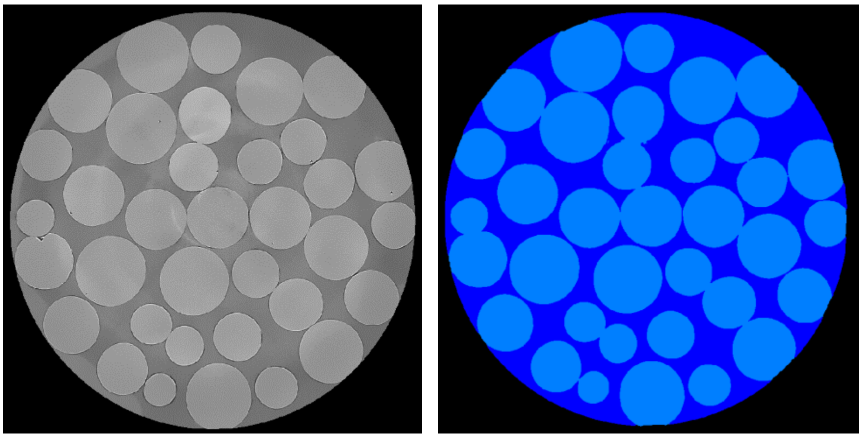

Figure 1 – (Left) Raw image of glass beads (left) and the correspondent segmented image (right). The sample diameter is approximately 4 mm and the pixel size is 3.2µm.

An alternative for this time-consuming segmentation is the use of TWS, which was applied to the dolomite sample. The data has a dimension of 1024x1024x845 and took only a few hours for the whole final segmentation: 1h20 was needed to the first training of the classifier (3578,9 seconds), 22 minutes for each retraining (1347,2 seconds). After this, this model is applied to the whole image and the final segmentation is reached. Figure 2 (left) presents the raw image of an oil/water saturated dolomite and a 3D rendering of a single pore (right).

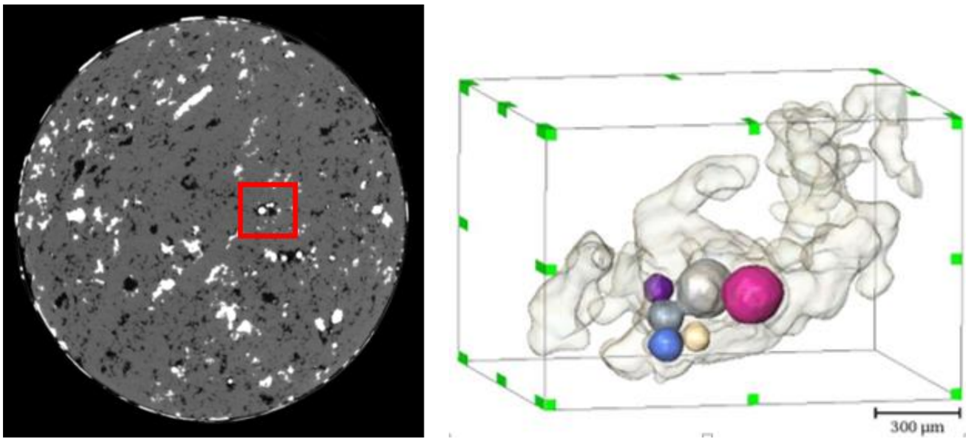

Figure 2 - Example of a carbonate rock (left) saturated with a NAPL phase (bright) and water (dark phase) and (right) the 3D rendering of the segmented pore space with the fluid inclusion.

CONCLUSION

With the advances of remediation techniques, the pore scale visualization of the contaminant displacement process becomes fundamental. The high resolution X-ray tomography allows the internal investigation of a sample without destroying it and, depending on the image resolution, it is also possible to resolve the pore space, identify and quantify different saturating liquids within them.

The process of segmentation allows de determination of pore surface area, volume, connectivity, and many other microproperties of individual pores. In the case of saturated pores spaces, it is also possible to reveal and distinguish the different saturating phases, such as oil, contaminants, water, gas, etc. For groundwater application, volumetric quantification and spatial location of the contaminants is fundamental to improve the remediation process.

Although manual and semi-automatic mechanisms of segmentation are time-consuming, high quality image is now being used to train different machine learning models to decrease the time, such as the example of dolomite rock. The main goal is evolving the technique to provide an even more detailed and complete data from 4D X-ray tomography, which allows the 3D study, in real time, of any type of fluid flow in porous media.

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