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Case study

Processing of rock core microtomography images: Using seven different machine learning algorithms

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ABSTRACT

The abilities of machine learning algorithms to process X-ray microtomographic rock images were determined. The study focused on the use of unsupervised, supervised, and ensemble clustering techniques, to segment X-ray computer microtomography rock images and to estimate the pore spaces and pore size diameters in the rocks. The unsupervised k-means technique gave the fastest processing time and the supervised least squares support vector machine technique gave the slowest processing time. Multiphase assemblages of solid phases (minerals and finely grained minerals) and the pore phase were found on visual inspection of the images. In general, the accuracy in terms of porosity values and pore size distribution was found to be strongly affected by the feature vectors selected. Relative porosity average value of $15.92 \pm 1.77\%$ retrieved from all the seven machine learning algorithm is in very good agreement with the experimental results of $17 \pm 2\%$, obtained using gas pycnometer. Of the supervised techniques, the least square support vector machine technique is superior to feed forward artificial neural network because of its ability to identify a generalized pattern. In the ensemble classification techniques boosting technique converged faster compared to bragging technique. The *k*-means technique outperformed the fuzzy *c*-means and self-organized maps techniques in terms of accuracy and speed.

1. Introduction

Numerous researchers have recently numerically determined petrophysical properties from X-ray microtomographic images. This digital rock physics (DRP) approach using rock images has allowed physical phenomena that cannot yet be measured in the laboratory to be simulated. DRP models can be used to determine realistic distributions of multi-component fluids, such as occur during imbibition and in Haines jump mechanisms (Berg et al., 2013), and to determine effective transport properties, such as the permeability tensor (Khan et al., 2012). These capabilities, coupled with the advanced computational algorithms that are available to interpret images, visualize three-dimensional (3D) images, characterize structures, and determine physical properties from images, have allowed the numerical DRP laboratory approach to be used to study the properties of real heterogeneous geomaterials (Andrä et al., 2013a,b).

Several important processing steps are required to allow a virtual rock-physics laboratory approach to be used. The first step is to perform a computer tomography (CT) scan of the selected rock sample at a high spatial (and eventually also temporal) resolution. Accurate phase segmentation, which can be complicated for a strongly heterogeneous material; eventually to allow an appropriate digital rock model to be built (Fusseis et al., 2014). The segmentation problem is reduced to the need to quantify the binary solid–void phase distribution (i.e., a binarization problem) when modeling fluid transport at the pore scale. However, Leu et al. (2014) recently performed a sensitivity study in which they showed that even a small bias in the accuracy of the binarization may lead to a significant error in the calculated permeability. Binarization is an essential prerequisite of DRP studies, but there are few accurate and fast binarization algorithms that are not biased by manual (subjective) interventions by the user. Choosing an appropriate scheme to binarize an image is key to characterizing a porous space with a good degree of accuracy and therefore decreasing the magnitudes of the uncertainties involved in

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determining the geometries of pore networks.

In general, an X-ray CT (XCT) image, or tomogram, consists of a cubic array of reconstructed linear X-ray attenuation coefficient values (also known as pixel values) that have to be quantified by analyzing the image. Analyzing the image involves four main tasks, namely filtering the image, segmentation, classification, and interpretation or modeling. In segmentation similar pixel values are clustered in to distinct group or classes, using unsupervised learning techniques. Whereas, for classification, using set of predefined features or classes (known as training data) similar pixel values are sorted out from unknown data set (testing data) using supervised learning techniques. These tasks are not independent of each other, but the classification and interpretation tasks determine which of the many available filtering and segmentation routines should be used. The accuracy of the segmentation process clearly determines the reliability of the resulting DRP model. Advanced segmentation routines can be performed when the sinograms are modified (Jovanović et al., 2013) or segmentation can be performed using clustering analysis, which is an unsupervised classification technique, where no manually specified sample regions need to be defined, or discriminant analysis, which is a supervised classification technique (Jain et al., 1999). Cortina-Januchs et al. (2011) used a novel segmentation and classification technique based on a combination of clustering analysis and an artificial neural network (ANN). Their approach offers advantages when used on large datasets, such as those with high spatial resolutions (e.g., sub-micrometer resolutions). Three different clustering algorithms (*k*-means, fuzzy *c*-means (FCM), and self-organized maps (SOM)) were used to segment the pixels in the tomographic images into groups of similar intensities. An ANN classification routine was then used, and this routine was highly modular and flexible and efficiently recognized patterns (e.g., accurately differentiating between solids and voids). Up to 97% of the pore spaces in the soils that were tested were correctly classified from the images that were acquired.

In this paper we propose a method with some modifications and improvements compared to the ones used by Cortina-Januchs et al. (2011). The particular improvements made are that the detection (segmentation) of pore space in our method is performed using 3D greyscale intensities, and three discrete machine learning algorithms are now used for the quantitative intercomparison process. It is to be noted that – all the investigated methods are global, i.e. only gray scale information is processed and neighborhood information is ignored (e.g. connectivity, regularity or local gradients).

A flowchart of the method is shown in Fig. 1. A comparative case study of unsupervised learning classifiers (*k*-means, FCM, and SOM), supervised learning classifiers (FFANN, least square support vector machines (LS-SVMs)), and ensemble classifiers (boosting and bagging) was performed. In the case of unsupervised classification, initial centroid values, membership function, topology and distance function had to be initially set. Whereas, for the supervised classification, required the user to determine representative areas for each class in order to get a priori knowledge about the class statistics. Our goal was to identify the advanced learning scheme that was best at segmenting the pore space and most accurate at determining the porosity.

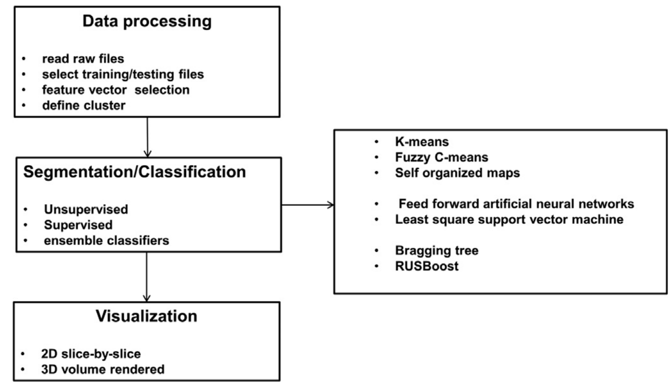

Fig. 1. Schematic illustration of our proposed method.

2. Materials and methods

2.1. Rock sample

An Andesite rock sample, as shown in Fig. 2, was used in the study. The sample was collected from Tongariro National Park, New Zealand. The sample had a porphyritic texture with large plagioclase crystals (up to 3 mm in diameter), pyroxene in a cryptocrystalline matrix, and isolated vesicles up to 6 mm in diameter. X-ray diffraction analysis confirmed that the sample contained 85% plagioclase and 15% pyroxene. The sample had an average grain density of 2.75 g cm^{-3}, measured using an AccuPyc II 1340 helium pycnometer (Micromeritics Instrument Corporation, Norcross, GA, USA), and an effective porosity of $17 \pm 2\%$, measured using a GeoPyc pycnometer (Micromeritics Instrument Corporation).

2.2. Image acquisition and processing

An image of a cylindrical rock sample with a diameter of 30 mm was acquired using a custom-built XCT scanner based on a CT-Alpha system (ProCon, Sarstedt, Germany) at the Institute for Geosciences laboratory in Mainz, Germany. The XCT scanner consisted of a Feinfocus microfocus X-ray tube (Yxlon, Hamburg, Germany) with a diamond-coated anode target with a focal spot size of a few micrometers. The X-ray data were acquired using a 2048×2048 pixel (called '2*k*') flat panel CCD detector measuring 105 mm × 105 mm (Hamamatsu Photonics, Hamamatsu, Japan).

The XCT scanner was calibrated using a monophasic pure aluminum reference cylinder with a diameter of 30 mm. The Andesite sample was then scanned using a source voltage of 125 kV. The sample was placed 162 mm from the detector panel, giving a final resolution of 13.6 µm per pixel. The sample was rotated in steps of 0.30°, giving 1200 projections to acquire data for the whole 360°, and the exposure time at each step was 0.2 s. Beam hardening correction using hypersurface fitting was performed to make the datasets segmentable (Jovanović et al., 2013). The rock sample projections were then Radon-transformed to give sinograms and then converted into tomograms using the back projection method (Feldkamp et al., 1984). The stacked tomograms produced were 16-bit 3D images, and the voxel resolution was 13.6 µm.

Each 16-bit 3D reconstructed raw image had 2048^3 voxels. The selected image filtering techniques were tested on all of the raw greyscale images before the segmentation algorithm was initiated in order to determine whether the image filtering techniques caused the signal-to-noise ratio to change significantly (Fusseis et al., 2014; Leu et al., 2014). The image characteristics, such as noise, blur, background intensity variations, brightness, contrast, and the general pixel value distribution, were not noticeably improved by applying any of the image filtering techniques. This can be attributed to the high quality and high resolution of the raw data.