Digital Rock Physics for Sands and Shales

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ABSTRACT

The Digital Rock Physics (DRP) technology is based on a rigorous numerical simulation of physical experiments in a realistic pore space, at the pore-scale level. The output is usually a macroscopic property conventionally measured in the lab. For example, single-phase viscous fluid flow simulation through a digitized pore space provides absolute permeability. A simulation of electrical current provides conductivity, and a simulation of the stress field provides the elastic moduli and strength. DRP complements lab measurements and, at the same time, enormously enhances the geoscientist’s capabilities because digital experiments can be conducted in real time and on small fragments of rock, such as drill cuttings.

We apply DRP to thin section images obtained from small fragments of sand and shale drill cuttings. The 3D digital pore space needed for numerical simulation is recreated from 2D images by means of statistical simulation. An example is also presented where the 3D digital pore space was obtained by direct CT scanning of a small rock fragment. The resulting macroscopic rock properties are compared to independently obtained lab and log data.

INTRODUCTION: BACKGROUND AND TECHNIQUES

Porosity and permeability are sediment properties most relevant to petroleum industry and environmental applications. Porosity determines how much fluid can be stored in rock and permeability determines how fast it can flow. Permeability is arguably the most elusive bulk property of sediment. Its detailed distribution cannot be measured in-situ. Decades of analysis of numerous laboratory data points failed to produce universal and robust transforms between permeability and other rock properties such as porosity, lithology, and texture. The reason is the extreme variability of the pore space topology in rocks. This variability is caused by two principal factors: (a) variations in deposition and (b) variations in diagenesis. The most reliable, and, essentially, the only way of measuring permeability is in the lab, by placing a plug of rock in a holder and measuring
In this work, we adopt the concept of virtual (or numerical) experimentation. Specifically, we simulate viscous fluid flow through a realistic pore space numerically represented by zeros (pores) and ones (mineral phase). One advantage of virtual experimentation over physical experimentation is that the former is non-destructive, i.e., a 3D pore space structure can be reconstructed from very small rock fragments such as drill cuttings. Also, a 3D pore space can be reconstructed from side-wall plugs which often cannot be used for physical permeability measurements because of the damage during plug recovery. Finally, once a 3D numerical representation of a pore space is placed in the computer, it can be numerically altered to reflect variations in diagenesis and sorting. By so doing, the virtual experimentalist can tremendously expand the database, without using additional physical material.

Attempts of directly estimating permeability by simulating fluid flow in a pore space have been undertaken in the past. However, complex pore geometry often makes modeling and simulation of transport properties in porous media very difficult. Conventional methods are usually based on partial differential equations, but the implementation of these techniques becomes intractable in a realistic pore space because of the no-slip boundary condition that has to be honored at the pore walls. As a result, simplified geometry is often used where pores are replaced with pipes (the so-called network models). Network models have been extensively used to simulate fluid flow at the pore scale. The most recent and advanced results of simulating fluid flow for a realistic pore space configuration are by Bryant et al. (1993) and Cade et al. (1994). Their approach is to approximate a complex pore space with a set of idealized geometrical figures. Such approximations are limited and often non-unique. The actual pore structure is obscured and it is rather difficult to model complex or irregular pore geometries. The results become heavily dependent of the approximation used to represent the pore space and many “free” parameters, such as the pipe hydraulic radius. Essentially, by using network models, one can arrive at any desired result and match any experimental data. Such a virtual experimentation tool is not predictive.

A robust and simple computational tool that can directly handle a complex 3D pore space without adjusting any free parameters is needed for virtual experimentation. One of such tools is the Lattice-Boltzmann method (LBM) that is based on statistical description of fluid flow phenomenon. LBM describes fluid flow as collisions of imaginary particles that are much bigger than water molecules. The collision rule preserves mass and momentum and is implemented on a 3D lattice superimposed onto a realistic pore space.

Fluid "particles" propagate on a discrete lattice and collide at lattice sites. A lattice site may be located in the pore space or inside a solid phase. Fluid particles move only
among the lattice sites that fall into the pore space. These particles bounce off the boundaries drawn midway between the pore-space and solid-phase lattice sites. Collision rules for particles in pore space and rules for collisions with solid boundaries are derived from the linearized Boltzmann equation to simulate Navier-Stokes equations of viscous flow. It has been shown (e.g., McNamara and Zanetti, 1988; Ladd, 1994) that the behavior of particles governed by such a collision rule is, in the limit, equivalent to the behavior of viscous fluid described by the Navier-Stokes equation for steady-state non-inertial (very slow) viscous fluid flow. LBM is a predictive tool because a lattice, if it is fine enough, can be implemented on a pore space of any complexity, without any simplification. The LBM tool can be directly used on a 3D numerical representation of a realistic pore space, such as shown in Figure 1.

![Figure 1. 3D pore space of sandstone. Grains (ones) are in red and the pore space (zeros) are in white. The image comes from 3D CT-scanning of a sandstone sample. After Keehm et al., 2001.](image)

The essential feature of LBM is the decoupling of the computational complexity of the numerical scheme from the geometrical complexity of the pore structure. Once the numerical scheme is implemented, flow may be simulated in any pore geometry, regardless of complexity, merely by classifying grid points either as rock matrix or pore space. The easiest implementation of LBM is for one-phase flow to compute absolute permeability. However, it can also be implemented to simulate a two-phase flow to compute relative permeability.

This numerical technique for one-phase flow has been perfected by Bosl (e.g., Bosl et al., 1998). Current speed of calculations allows one to calculate the permeability of a $10^6$-cell digital sample within seconds on a modern PC. Bosl’s numerical implementation is used in the below examples.
The most direct way of obtaining a 3D digitized representation of a pore space is by CT-scanning a small sample of rock (e.g., a drill cutting). Figure 2 (left) shows the raw CT scan of a sandstone plug. The variation in color intensity reflects variations in density. Because of the large density contrast between the mineral phase and the pore space, it is straightforward to convert a CT image into a 3D binary pore space representation in the computer (Figure 2, right).

![Figure 2. Left -- Raw CT scan of a sandstone sample. Pores show as dark patches embedded in the mineral phase (green). The apparent layering in the sample is an artifact of digital representation. Right -- A binary image (zeros and ones) of a small portion of the 3D pore space, part of the sample shown on the left (Kameda, 2002).](image)

A similar CT-scan image can be obtained from an unconsolidated friable sand sample impregnated by epoxy to hold the grains together (Figure 3, left). Because of the large density contrast between epoxy and minerals, the former shows as the pore space so that the original pore space can be easily separated from the grains in the computer (Figure 3, right). Numerical experiments using LBM can be immediately conducted on a true 3D image. Our analysis indicates that numerical results match the physically measured permeability. Also, the original image can be altered to simulate diagenesis and the corresponding porosity and permeability can be calculated accordingly.

3D pore space can be also obtained from 2D microscopic images of rock. Consider a 2D slice of porous material, such as a thin section (Figure 4, left). A 2D digitized image of a thin section can be numerically converted into a binary 2D image represented by pixels with “1” assigned to the pixels that fall into the pore space and “0” assigned to the pixels that fall into the solid phase (Figure 4, right).
Keehm et al. (2001) show that the 2D image statistics (porosity and the variogram) can be used to statistically reconstruct a 3D pore space from its 2D slice via statistical indicator simulation (Deutsch and Journel, 1998). This reconstruction method is commonly used in geostatistics to fill a 3D volume with properties known at the wells. Here we use it to fill 3D space with zeros and ones in accordance with the statistics extracted at a thin section that bounds this 3D space. The resulting reconstructed 3D pore space has a realistic configuration (Figure 5).

Figure 3. Left – Friable sand stabilized by epoxy. Right – Its CT scan showing grains, in gray, and pore space, including the epoxy, in black (Kameda, 2002).

Figure 4. Left – A digital photograph of a sandstone thin section. Right – The same thin section image-processed to highlight the pore space (blue) and grains (black).
The most important control of whether a statistical reconstruction of 3D pore space from a 2D image is suitable for permeability calculation is the final result. In other words, the ultimate criterion is the math between the permeability obtained by applying the LBM tool to a statistically reconstructed image and permeability physically measured on the same sample.

Figure 6. Calculated permeability (LBM flow simulation) versus measured permeability in high-porosity and low-porosity sandstones. The numerical permeability has been calculated from 2D thin sections by first reconstructing 3D pore space via statistical indicator simulation and then applying the LBM technique to the resulting 3D virtual sandstone samples.
The results that we have obtained on a number of sandstone samples in a porosity range between 5% and 35% show that by using a statistical reconstruction of 3D sandstone from a 2D image and consequently applying LBM gives realistic permeability values close to the actual permeability data (Figure 6).

The Digital Rock Physics technology can go far beyond estimating permeability from microscopic images of rock. The same numerical simulation approach as in permeability calculation can be used to estimate the electrical and elastic properties of rock, and even rock strength. Below we give examples of P- and S-wave velocity estimations for shale where a combination of numerical and analytical modeling is used.

**SHALE SAMPLES: PROPERTIES AND IMAGES**

The three shale samples selected for this work have relatively high-porosity and mostly consist of clays, kaolinite, smectite, and illite. Well log data are available for the cored interval. Of specific interest to us are the sonic data from which we estimated the P-wave velocity range in the shale samples under examination.

Below, in Table 1, we summarize the data available from porosity and mineralogy laboratory measurements as well as P-wave sonic velocity data from well logs.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Porosity</th>
<th>Feldspar</th>
<th>Smectite/Illite</th>
<th>Kaolinite</th>
<th>Siderite</th>
<th>Pyrite</th>
<th>Vp (km/s)</th>
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<tbody>
<tr>
<td>A</td>
<td>0.24</td>
<td>0.04</td>
<td>0.37</td>
<td>0.49</td>
<td>0.05</td>
<td>0.05</td>
<td>2.400</td>
</tr>
<tr>
<td>B</td>
<td>0.20</td>
<td>0.14</td>
<td>0.25</td>
<td>0.50</td>
<td>0.06</td>
<td>0.05</td>
<td>2.550</td>
</tr>
<tr>
<td>C</td>
<td>0.23</td>
<td>0.05</td>
<td>0.40</td>
<td>0.49</td>
<td>0.06</td>
<td>0.00</td>
<td>2.628</td>
</tr>
</tbody>
</table>

The thin sections of the shale samples have been prepared and photographed (Figures 7 – 9). The images have revealed important structural features of the samples. However, it was impossible to identify the pore space from these images because of the extremely small size of the clay particles which cannot be easily identified through conventional microscopy.

To resolve the pore space in the shale samples under examination, we resorted to scanning electronic microscopy (SEM). The SEM images of the three samples taken at different degree of magnification, reveal the complex structure of the pore space, defined mostly by microscopic clay particles (Figures 10 – 12).

The resolution needed for identifying the pore space of clays is on the order of 1 to 10 micron. A very high-resolution image of Sample C (Figure 13) reveals the extremely complex pore space structure between clay platelets.
Figure 7. Thin section of Sample A.

Figure 8. Thin section of Sample B.
Figure 9. Thin section of Sample C.

Figure 10. SEM image of Sample A. Courtesy Manika Prasad.
Figure 11. SEM image of Sample B. Courtesy Manika Prasad.

Figure 12. SEM image of Sample C. Courtesy Manika Prasad.
Permeability calculations have been conducted on the three selected shale samples by consequently using image processing, statistical indicator simulation reconstruction of 3D pore space from 2D images, and, finally, the Lattice-Boltzmann fluid flow simulation. Figures 14 shows a snapshot of the software panel and permeability calculation results for Sample A. The same software and work flow have been for Samples B and C.

The permeability of the shale samples, as expected, is very low in spite of relatively large porosity. This is apparently due to the very small size of the individual particles and the corresponding very large specific surface area.

The permeability values are given in Table 2. The range of permeability is between 0.04 and 0.14 mD which is about five orders of magnitude smaller than in sands of comparable porosity. The observed small permeability difference between the three shale samples is most likely due to small particle size variation between them.

Velocity calculations have been conducted using porosity data as calculated from SEM images, combined with the uncemented sand/shale model of Dvorkin and Nur (1996). The model curve shown in Figure 15 captures the velocity-porosity behavior of the samples under examination. This model can be accurately calibrated where porosity

Figure 13. SEM image of Sample C at very high resolution. Courtesy Manika Prasad.

**SHALE SAMPLES: CALCULATING PERMEABILITY AND VELOCITY**
and mineralogical make-up of the rock are determined from mudlog and microscopic images of drill cuttings.

In Figure 16 we plot the sonic velocity profile with selected laboratory velocity data points and DPR results superimposed. There is close agreement between the data from three independent sources.

Figure 14. Software panel with permeability calculation results for Sample A. The image of an image-processed SEM image is in the right-hand window where light-blue color indicates pore space and red color is for the minerals. The statistically reconstructed 3D rock is shown as a cube in the middle window. The permeability calculation results are in the right-hand window and in the bottom window.

<table>
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<th>Sample</th>
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<th>Permeability (mD)</th>
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<tr>
<td>A</td>
<td>0.24</td>
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<td>0.23</td>
<td>0.05</td>
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Figure 15. Velocity versus porosity for the three shale samples under examination and the uncemented sand/shale model curve.

Figure 16. Sonic velocity versus depth for wells B2 (blue) and B3 (red). Laboratory velocity data for two core samples from well B3 are shown as orange squares. DPR results that have been obtained from SEM shale images and rock physics modeling for three shale samples from well B3 are shown as yellow circles.
The rock physics velocity-porosity model used in this work has been tested in an extended interval of well B3. Figure 17, left, shows a sonic velocity versus porosity cross plot with a model curve superimposed. The curve used has been calculated for average clay content present in the interval. The spread of log data points around the model curve is due to local mineralogical variations. In Figure 17, left, we plot the P-wave velocity predicted in well B3 according to the rock physics model versus the measured sonic velocity. The model derived for average clay content accurately predicts the data.

![Figure 17. Well B3. Left -- Sonic velocity versus density-porosity (blue symbols) with an average model curve superimposed (red). Right – Predicted versus measured velocity. The spread of the data points around the model curve is due to local mineralogical variations.](image)

CONCLUSION

The digital rock physics technology combined with powerful microscopy tools and theoretical rock physics opens an avenue for determining such important rock properties as porosity, permeability, and velocity from small rock fragments, including drill cuttings and sidewall plugs. The technology can be applied to rock samples in real time, depending on the availability of accurate imaging tools at the site.

ACKNOWLEDGMENT

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REFERENCES


