MULTI-SCALE PERMEABILITY TRENDS USING DIGITAL ROCK PHYSICS

R. Sungkorn, V.A. Gundepalli, Y. Mu, A. Grader, C. Sisk, S. Bhakta, N. Derzhi, J. Dvorkin, J. Toelke
Ingrain Inc., 3733 Westheimer Road, Houston, TX 77027, U.S.A.

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ABSTRACT

We proposed a workflow for porosity-permeability and porosity-formation factor trends upscaling based on digital rock physics. The workflow consists of three important parts that integrate information between coarse and fine scales. First, building blocks, i.e., unique rock fabrics presented in a reservoir rock sample, are extracted based on statistics derived from a 3D coarse scale image. Next, one or several high resolution 3D fine scale images of all building blocks are used to derive their fine scale permeability and formation factor trends. Then the fine scale trends of each individual building block are used to populate each voxel of the 3D coarse scale image with permeability and electrical conductivity. This procedure takes into account the variation of conductivity and permeability within a building block on the coarser scale and frees us from applying only a single value in each building block. This procedure can be applied recursively to cover the whole range, e.g. from nano-CT images up to the whole core CT-images.

The capability of the workflow is demonstrated first with artificially generated rocks. The results suggest up to 50% error in permeability prediction when the workflow is not integrated. Then, a study of a real reservoir rock with the proposed workflow opens a new level of understanding of permeability from building blocks up to plug scale. The accuracy of the workflow is confirmed with a laboratory measurement.

INTRODUCTION

It is well known that rocks in recently-discovered reservoirs inherit high degree of heterogeneity and scale-dependence, examples include carbonate reservoirs. To complicate matters further, the length scale that defines properties of the sample can span several orders of magnitude, see Figure 1 for an illustrated example. A digital rock physics-based workflow that can accurately upscale petrophysical properties from the fundamental unit of rock samples to a desired scale, e.g. core and log scale, is one of the important challenges in oil and gas industry. The obtained results should be able to apply directly or in combination with reservoir simulations to assess sensitivity and robustness of reservoirs.

Multi-scale effects on petrophysical properties have been studied by scientists and engineers. Grader et al. [1] employed multi-scale imaging techniques to acquire images of carbonate rocks at various resolutions. High resolution images were used to compute petrophysical properties, e.g. porosity, absolute and relative permeability. The work was one of the first pioneer works to demonstrate the potential of digital rock physics. Serag El Din et al. [2] performed measurements of carbonate samples ranged from small trims to whole core samples. They observed differences in permeability and cementation exponents measured on different scales. They concluded that whole cores provide more representative measurements and decrease uncertainty in physical interpretation. Skalinski et al. [3] integrated three scales of petrophysical data using measurements and digital rock physics. The Darcy upscaling simulations were used to predict permeability of large scale samples. Recently, Khalili et al. [4] proposed an upscaling approach for permeability and formation factor using multi-scale x-ray CT imaging techniques, image registration technique and digital rock physics. Relations between porosity and permeability/formation factor were derived from a randomly selected size at various locations within small scale samples.

MULTI-SCALE UPSCALING WORKFLOW

Earlier mentioned works (and references therein) formed an important basis for petrophysical properties upscaling. However, remaining issues needed to be solved are:

1. Proper selection of sample size and locations
2. Realistic relation between scales, i.e. upscaling
3. Multi-scale solution of multi-scale phenomena.

In this work, we propose a workflow based on digital rock physics that properly upscales petrophysical properties and solves the issues addressed above. The main idea is adopted from the large eddy simulation (LES) concept in computational fluid dynamics (CFD). That is, a cut-off in length scale is introduced. Phenomena larger than the cut-off length are resolved explicitly while the phenomena smaller than the cut-off length are captured by models. The proposed workflow can be described in three parts (see Figure 2):

1. ***Find building blocks***. In this part, unique rock fabrics present in the rock sample are extracted based on statistics derived from a larger scale, Figure 2(a) and (b). At the smallest scale the statistics of pore morphology such as porosity, surface to volume ratio and Minkowski's measures may be used. On the other hand, at a larger scale, statistics of CT number may be used. An example is given in Figure 1 (center) where two types (building blocks) of porous matrix are defined (i.e. matrix B_1 and B_2). Note that this part can be considered as a digital image analysis process to identify patterns based on rock morphology and/or rock properties using a proper machine learning approach.
2. ***Extract petrophysical relation***. After the building blocks are properly defined, a high resolution 3D image of each building block is acquired. Dimension of representative elementary volume (REV) of each 3D images is extracted based on desired statistical properties. The dimension is used to select proper locations for digital subdivision. Typically, 50 to 300 digital subdivisions are used to extract relations between petrophysical properties (i.e. trends) such as porosity-

permeability (and porosity-formation factor), Figure 2(c). The previous and current step provide *a proper selection of sample size and location*.

3. ***Trends upscaling***. In order to relate properties between scales, a connection must be established. For example, the relation between CT intensity of the area/volume that the high resolution image is taken and the CT intensity of the high resolution image may be used to generate multi-scale relation, Figure 2(d). The exact location may be identified using an image registration technique. Then, desired petrophysical properties extracted from high resolution image are populated on the large scale sample, Figure 2(a), based on their building blocks and multi-scale relation. In contrast to conventional approaches where only single value is assigned to each building block or segmented group, the workflow provides *a more realistic upscaling of petrophysical properties*.

The workflow introduced above is not limited to upscaling between two scales. It can be used recursively to cover the whole range from, e.g. nano-CT images up to whole core CT-images.

Another important ingredient of the proposed workflow is to *extract multi-scale petrophysical properties by solving multi-scale governing equations* (in analogy to the LES approach). An example is the absolute permeability. At the smallest scale where only impermeable material and pore space exist, see Figure 1(right), fluid flow is resolved based on the Stokes equation (given low Reynolds (Re) number flow condition in this example). In a rock with high Re number, the Navier-Stokes equations can be used to resolved fluid flow. However, at a larger scale, e.g. the sample in Figure 1(center), fluid flow takes place at multiple scales: at the so-called Darcy scale in porous matrices and at the scale of image resolution in pore space. Here, the Brinkman–extended Darcy (B-D) equation can be considered. The B-D equation resolves fluid flow in pore space while the flow in porous matrix is modeled through the Darcy equation. In our work, we use lattice Boltzmann (LB) scheme to solve the B-D as well as the Stokes equations. The LB scheme is implemented on multiple graphic processing units (GPU) to shorten the simulation time within the order of hours. See Toelke & Krafczyk [5] and Ginzburg [6] for detailed discussion about the LB scheme and the GPU implementation.

The workflow can be different based on several factors, e.g. rock type and sample scale. However, typical workflow starts with a three-dimensional image of a desired-scale sample, e.g. core scale. Number, location and size of building blocks are derived from the core sample. During this step, the sample is also segmented based the identified building blocks. The variation within the building blocks may be defined based on, e.g. locally-average CT number. Then, finer-scale (e.g. plug) three-dimensional images of the identified building blocks are taken. Fine scale trends of petrophysical properties are derived digitally from the finer-scale sample. Using an image registration technique and a comparison between fine and large-scale image properties, the fine scale trends (from plugs) are populated on the large scale sample (core).

MULTI-SCALE ROCK PERMEABILITY

We artificially created two fine scale rock samples (i.e. simple digital models). One with intersecting slit in 3D and another with pore body and pore throat structure. Part of the samples are shown in Figure 3 (left) at the top and bottom, respectively. The sample dimension is 1 x 1 x 1 [mm] in both cases. The pore size increases in all direction resulted in channel size between 4 and 14 micron for the first sample (hereafter called fine sample 1). Pore throat size increases between 7 and 22 micron while the pore body is kept constant in the latter sample (hereafter called fine sample 2). Permeability trends of both samples are simulated using the procedure described above. As expected, permeability of the first sample increases slowly with porosity while the increase is more rapid in the second sample. Power law fitting results in an exponent of 3.2 and 7.3 for the first and second sample, respectively.

Next, we generated a large scale digital sample with a dimension of 25 [mm] in all directions. Properties of the fine sample 1 and 2 are assigned to two group of voxels in the large scale sample. The above fine scale samples are combined in series, parallel and diagonal (see Figure 3 (right)). A variation of porosity (and hence permeability) is populated based on the trends obtained from fine scale samples (Figure 3 (left)). Porosity variation in the samples are illustrated in Figure 3 (left). In a natural rock sample, large-scale variation of petrophysical properties within a building block is populated based on finer-scale relations. As a result, the populated properties are based on, e.g. pore morphology and/or pattern of rock fabrics. Another set of simulations is carried out using the same geometry without variation of porosity (as in a traditional upscaling procedure). Here, averaged permeabilities of the fine samples are used. The predicted permeability from both cases are plotted in Figure 3 (right). It can be easily seen that the samples with porosity variation have permeability lower than the samples without variation. The permeability error ranges from 20% in the parallel setting to 29% and 42% in diagonal and series settings, respectively.

CONCLUSION

- Building block concept provides a basis for characterizing heterogeneous reservoir rocks.
- Proper selection of size and location of digital subdivisions accurately capture relation between petrophysical properties.
- A realistic upscaling of petrophysical properties can be done by, first, correlating images at different scales. Then, trends derived from the smaller scale images are used to populate the petrophysical properties on the larger scale image based on variation within building blocks.
- In order to obtain multi-scale petrophysical properties, multi-scale governing equation must be employed.
- Applications of the workflow include, but not limited to:
    - Generating trends (e.g. porosity-permeability) using fewer samples than laboratory-based methods (in one of our cases, up to two order of

magnitude fewer). It is recommended to use the workflow along with a few laboratory results to increase level of confidence.

- The workflow can be used in combination with the well log to improve the interpretation.
- The derived information can be used as an input and/or additional information for reservoir simulations.

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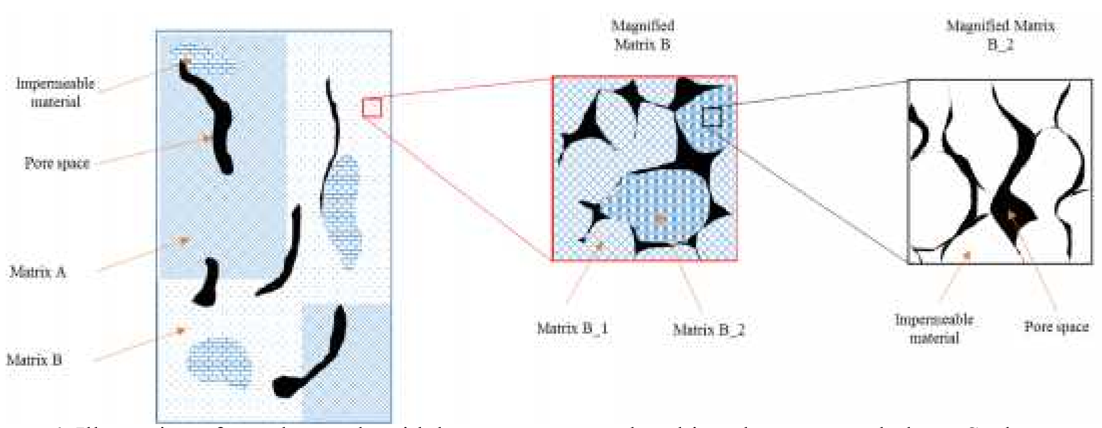

Figure 1. Illustration of a rock sample with heterogeneous and multi-scale pore morphology. Scale increases from left to right. A large scale rock sample with resolved pore space, impermeable material, and porous matrices labeled A and B (left). Magnified area of porous matrix B consists of pore space which is unresolved at the large scale and porous matrices labeled B_1 and B_2 (center). At high magnification, the porous matrix B_2 is fully resolved. It consists of pore space and impermeable material (left).

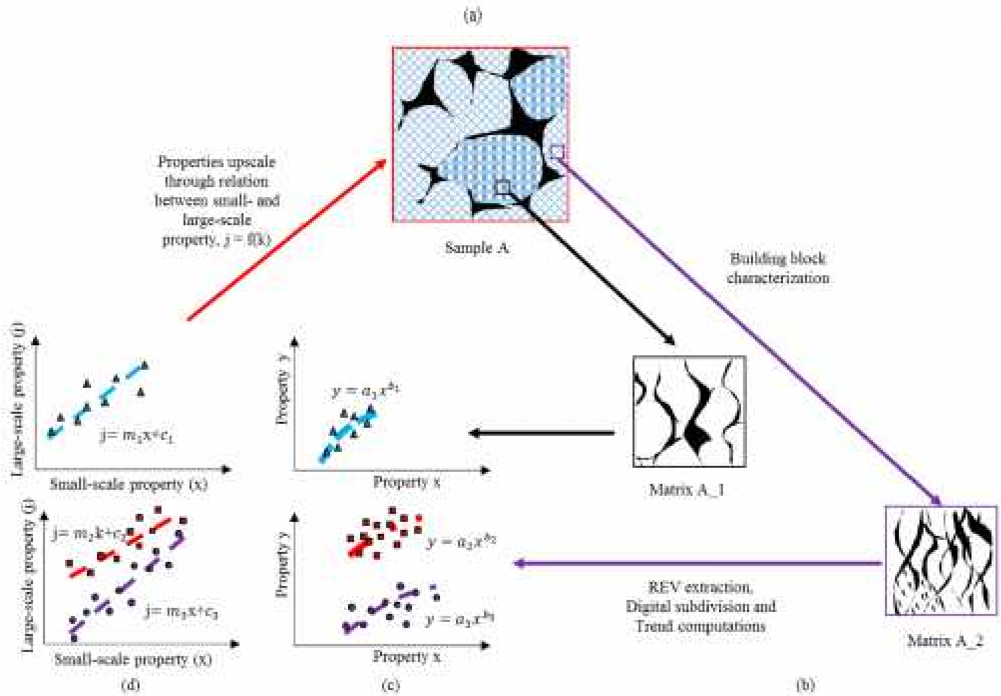

Figure 2. Schematic illustration of multi-scale petrophysical properties upscaling workflow. Building blocks are extracted from sample A (a). Trends are generated for each building block based on their high resolution images (b). Properties of all building blocks in sample A are populated using trends extracted from high resolution images (c).

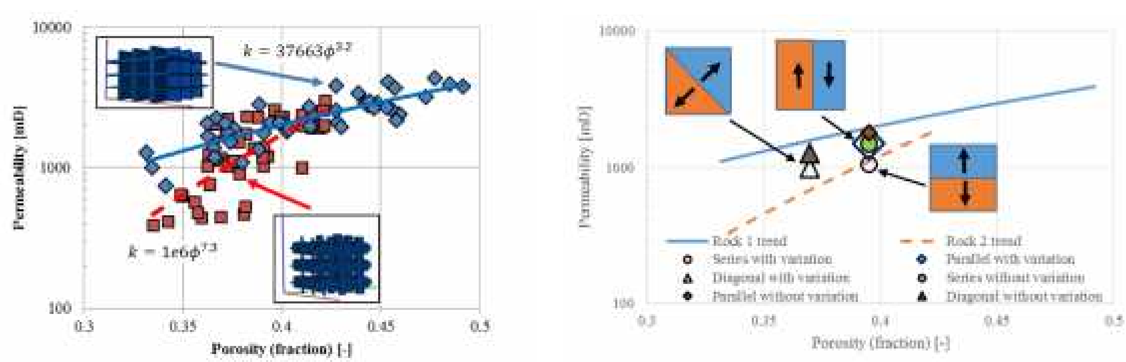

Figure 3: Fine scale porosity – permeability trend (relation) created by the digital subdivision process for two artificial rocks (left). Upscale permeability of large scale artificial plugs generated by combining the fine scale rocks (right). Porosity increase following the direction of the arrows.