VALIDATION OF METHODS FOR MULTI-SCALE PORE SPACE RECONSTRUCTION AND THEIR USE IN PREDICTION OF FLOW PROPERTIES OF CARBONATE

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ABSTRACT

The creation of a 3D pore-scale model of a porous medium is an important step in quantitatively characterising the medium and predicting its two-phase and three-phase relative permeabilities and capillary pressures. Recently, we have developed pore architecture models (PAMs) to reconstruct 3D reservoir rocks from 2D thin section images along with a set of pore analysis tools (PATs) to quantitatively analyse the reconstructed pore systems. The PATs reveal the pore topology and geometry, from which we can construct pore network models and compare the original and reconstructed 3D microstructures. Compared to other published reconstruction and network extraction methods, the PAMs and PATs algorithms are computationally significantly more efficient.

In this paper we describe a series of tests involving rock PAM reconstructions and extracted networks, and compare the flow properties predicted using network flow simulations. Specifically, we validate the reconstruction method through "self-reconstruction"; i.e. we take numerical thin sections from a reconstructed rock or known 3D tomograph to create a new reconstruction, for which the properties are compared with the original. First, we consider a fairly homogeneous sandstone rock, for which good agreement is found between the original and the new reconstructions in terms of numbers of pores, pore size distribution and connectivity. The permeability of the sandstone example is also closely matched and, in addition, two-phase relative permeabilities for both drainage and imbibition agree well. Second, the reconstruction method is applied to more heterogeneous carbonate rocks. When such materials possess distinct pore systems with wide ranges of pore sizes, we overcome some of the difficulties of the multiple scales by integrating multiple reconstructions based on different resolution input images. Two-phase relative permeabilities are compared for the individual and the combined scale reconstructions. The results reported here indicate that the smaller elements of the pore system are important in governing aspects of the flow.

The above suggests that the reconstruction process produces a good representation of homogeneous and some heterogeneous rocks, although prediction of multi-phase flow properties in multi-scale rocks will require larger reconstruction volumes, which seem to be within reach of our efficient methods.

INTRODUCTION

Quantitative characterisation of porous media at the pore scale is of fundamental importance in many scientific subjects. The pore structure of reservoir rocks is complex, but the geometry and topology of porous rocks must be known if we wish to *a priori* predict the physical rock properties. The pore geometry ultimately affects many macroscopic phenomena associated with mechanical, acoustic and fluid flow responses.

Although direct measurements of 3D microstructures are now available via X-ray computed microtomography (Dunsmoir *et al.*, 1991; Spanne *et al.*, 1994; Hazlett, 1998; Arns *et al*., 2001), it is often difficult and expensive to obtain reliable "images" of the 3D pore structure. Such methods are also limited in terms of their scale of resolution because there is a trade-off between resolution and sample size, which in turn relates to sample representativity. Recently, workers at the Australian National University (ANU) have made significant progress in generating micro-CT images of the 3D pore space of carbonate rocks (Arns *et al*, 2005; Knackstedt *et al*, 2007). These images show the larger pores and vugs in carbonates but they do not fully resolve all of the microporosity which is present. As alternatives to CT methods, several techniques have been proposed to statistically generate 3D pore structures from spatial information derived from readily-obtained 2D images (Joshi, 1974; Quiblier, 1984; Roberts, 1997; Hazlett, 1997; Yeong and Torquato, 1998; Manswart and Hilfer, 1998). Quantitative comparisons of these models with tomographic images of sedimentary rocks have shown that statistical reconstructions may differ significantly from the original sample, in particular with respect to their connectivity (Hazlett, 1997; Biswal et al., 1999; Manswart et al., 2000). In another approach, Bakke and Øren (1997) have developed a process-based reconstruction procedure, which directly models the particle sedimentation process. This method was successfully applied to reconstruct Fontainebleau sandstone, but it involves intensive computing and it currently works only for rocks with a straightforward history that is primarily dependent on the original depositional texture

This paper is based on the work of Wu *et al.* (2006), who described a stochastic reconstruction method that can in principle overcome some of the fundamental problems of the above described methods. The new method creates reconstructions of a (possibly) heterogeneous porous medium using Markov Chain Monte Carlo (MCMC) simulation. The models are referred to as "pore architecture models", or PAMs. This approach differs in one important aspect from earlier two-point (or multi-point) correlation methods (e.g. Okabe and Blunt, 2004), in that it involves a multiple-voxel interaction scheme (a high-order neighbourhood system) to preserve structural characteristics of the input data. Moreover, the PAMs approach is non-iterative, which allows much faster computations and therefore generation of significantly larger reconstructions. In this paper we present s validation of the PAM reconstruction method using a "self-reconstruction" approach; i.e. we take numerical thin sections from a reconstructed rock or known 3D tomography to create a new reconstruction, for which the properties are compared with the original. The self-reconstruction is applied to a relatively simple sandstone sample.

For more complicated rocks, such as carbonates, with distinctive macropore (pore size in 10s μm to mm) and micropore (pore size in sub-μm to μm) systems, our 3D Markov random field models can be used to reconstruct representative systems at each scale. For a carbonate sample, thin section images have been obtained under different microscope magnifications, allowing PAMs reconstructions from which we extract networks for the coarse and fine scales. A method is proposed to combine the reconstructions from the coarse and fine scales. We extract networks for the coarse, fine and combined scales and we compare the predicted relative permeabilities at each scale.

3D PORE RECONSTRUCTION AT MULTIPLE SCALES

The PAMs method originates from Markov Random Fields (MRF) models (Geman and Geman, 1984). MRF methods are based on using only a small number of *local* conditions (derived from a training image) to predict global features. In typical usage, the training image is pixelated, and the probability of each pixel of the model being in a particular state (black or white, for example) is determined (or conditioned) by means of a transition matrix of conditional probabilities that is obtained from the training (prior) image. The general multi-point statistics scheme (e.g. Okabe and Blunt 2004) uses larger templates, but in that method, the probabilities of all possible templates must be determined, which is computationally expensive. The PAMs approach differs in one important aspect from the two-point (or multi-point) correlation methods (e.g. Okabe and Blunt, 2007) in that it involves a multiple-voxel interaction scheme (a high-order neighbourhood system) to preserve structural characteristics of the input data. Moreover, the Markov Chain approach is non-iterative, which allows much faster computations and therefore the generation of significantly larger reconstructions. The details of the PAMs method are described in Wu et al (2006). We have applied the PAMs approach to a wide range of rocks and soils, for >100 different materials to date (Wu *et al,* 2007). The measured permeabilities of these materials range over more than six orders of magnitude, and the materials exhibit both simple and complex pore systems. Although extensive validations have been carried out to validate the PAM reconstructions, e.g. they are visually similar in terms of morphology, the structural features are captured, the permeability is matched, etc, we are continuing to further test the robustness of the reconstructions and use multiple methods (PATs tool, LB and network extraction) to evaluate their material properties. In this paper, an emphasis is placed on validating PAMs by self-reconstruction, as described in the next section.

The PAM reconstruction procedure has proven to be relatively straightforward for the case of typical reservoir sandstones (Wu *et al*, 2006). However, some serious challenges arise when we consider more difficult rocks, such as carbonates, siltstones, and deformed rocks (Wu *et al*, 2007). The main difficulty arises from the fact that the pore system in these rocks has ***multi-scale*** features, e.g. macropores and micropores coexist, and therefore images at different scales have to be considered. The micropores can be observed in a fine-scale (submicron) images, while coarse resolution images have to be used to handle the macropores and fractures in a relatively large frame. Because of computer memory

limitations, we can only deal with a small volume for a 3D image (perhaps to ~500^3 voxels). If the model has macropores, then in a high resolution reconstruction, there would be only a few scattered large pores which would dominate the model. For example in Fig 4d, the reconstructed cube is 300^3 in volume of voxels and the resolution is 1 voxel = 0.14 microns. If we have micropores, at say 28 microns in diameter, located within the cube, then a single pore will take up about 214^3 voxels - 70 % of the volume of the cube. In addition, the transition probabilities, derived from the training image, would not properly represent the micropores because the variations occur at scales that are larger than our template. To overcome this problem, we here show an approach in which we sub-sample a small part of the training image at high resolution, focusing on the smaller pores, i.e. the high resolution training image does not contain any complete large (macro pores), and we reconstruct a separate model that gives a good representation of the micropore system.

In capillary dominated reservoir fluid flow calculation, micropores play an important role in multi-phase flow, and it is vital to understand the comprehensive flow system that results from a combination of macropore and micropore systems. In section 4 we will explain the method of integration from different scales.

VALIDATION OF PORE SPACE RECONSTRUCTION

In the validation by means of "self-reconstruction", we use two cycles of reconstruction to allow a comparison with their parent structure based on the geometry, topology and flow predictions: (i) the first reconstruction is run using 2D training images taken from a "reference" 3D tomographic image; (ii) the second cycle reconstruction is then based on 2D slices from the reconstructed structure. All the reconstructed 3D structures are analysed and compared in terms of the number of pore bodies and bonds, pore connections (coordination number), as well as the calculated absolute permeability and relative permeability.

The analysis of the 3D structure of these models uses the pore network extraction approach of Jiang *et al.* (2007). This method extracts the geometrical/topological network that represents the pore structure of a porous medium, referred to as the GT-network. The GT-network extraction algorithm involves a number of steps including: (a) calculation of the 3D Euclidean distance map; (b) clustering of voxels; (c) extraction of the network of the pore space; (d) partitioning of the pore space; and (e) computation of shape factors.

A two-phase flow network model has been developed (Ryazanov *et al,* 2008) that takes as input the extracted network and its properties. The model is similar to that of Valvatne and Blunt (2004), although compared to the latter a more accurate pore shape description has been included, as well as the (correct) thermodynamically-based criteria for collapse of oil layers in pore corners during imbibition.

The two-cycle self reconstruction is designed to test the error propagation of the PAM method. Due to the relatively small neighbourhood structure used in the PAM model for 3D

reconstruction, there is a trade-off between the efficiency and the accuracy of the pore morphology reproduction. Therefore, we might anticipate that there is some degree of degradation after each cycle of reconstruction. The general idea of this test is to see how much deviation will occur in each reconstruction cycle.

The First Cycle Reconstruction from Original 3D CT Image

For the first cycle of reconstruction, an input 3D reference structure is required. In our implementation, a 3D CT scanned image of a sandstone is used, with a volume of 300^3 voxels and a resolution of 5.6 μm, as illustrated in Figure 1a.

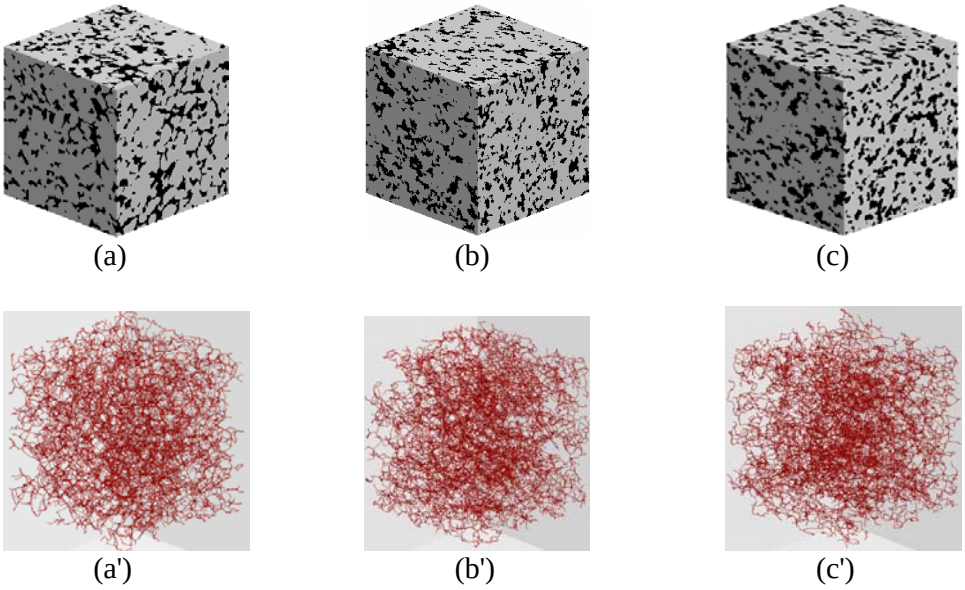


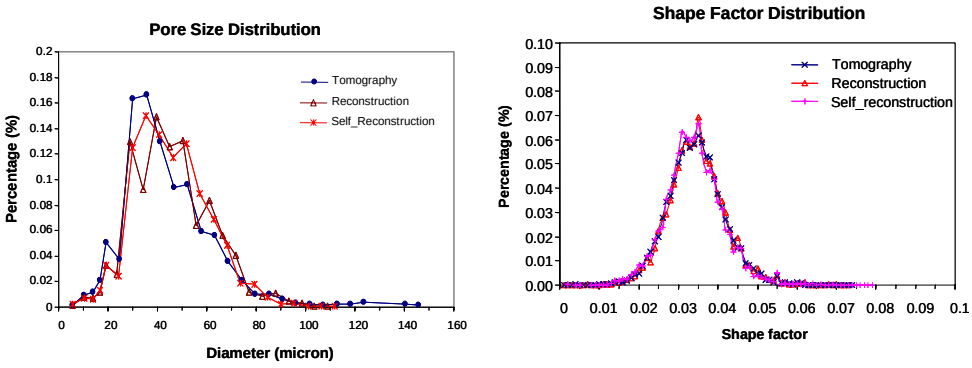
Figure 1. (a) The 3D CT image of sandstone with volume of 300^3 voxels, the resolution is 5.6 μm per pixel; (a') the extracted network from 3D image (a); (b) The first cycle reconstruction of sandstone and (b') pore network extraction; (c) the second cycle reconstruction (Self-reconstruction) of sandstone and (c') the extracted pore network.

The extracted network (Fig.1a') from the 3D CT image (Fig. 1a) has 2953 pores, 5256 throats and a coordination number of 3.51. The network-derived absolute permeability is 2509 mD.

2D slices in the x, y and z directions were randomly taken from the 3D tomography image for use as training images for the subsequent reconstruction. One realisation of the resulting PAM is shown in Figure 1b. Then we use PATs to extract the G-T network (Figure 1b'). The resulting network in Figure 1b' has 2913 nodes, 4953 bonds and the average coordination number of 3.34. The resultant network permeability is 2046 mD, which is 18% lower than that of the original rock from which the CT image was taken.

The Second Cycle Reconstruction from Reconstructed Structure

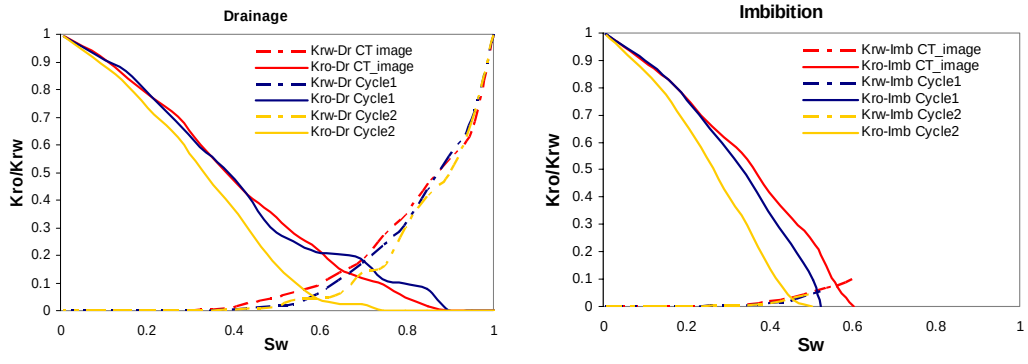
The second cycle reconstruction is carried out using thin sections taken from the already reconstructed image as training images, to achieve a so called "self-reconstruction". The self-reconstruction and the corresponding extracted G-T network is shown in Figures 1c and 1c' respectively. The G-T network has 2886 nodes, 4810 bonds and a coordination number of 3.28. The resultant absolute permeability predicted from the network flow model is 1514 mD, which is 28% lower than that of the first reconstruction, and 39% less than the permeability of the original model.



(a) (b)

Figure 2. Comparison of pore size distribution and shape factor distribution curves for the original reference 3D image, the reconstruction and the "self reconstruction".

The pore size distributions and shape factors (shape factor = area /perimeter^2) computed from these images are shown in Figure 2a and Figure 2b respectively, which show very close agreement. However, a small reduction is noted in the relative frequency of smaller pores as a result of the reconstruction process. This, combined with the reduction of bonds in the reconstructed networks, indicates that the smallest components of the pore system are being eliminated by the current method. Additional effort is needed to understand and correct this artefact. To allow a comparison of the two-phase flow properties of the original image and the reconstructed structures, the corresponding relative permeability curves (for water-wet systems) are displayed in Figure 3. Agreement is generally good, although a slight degeneration occurs, in particular for the oil curves. This is compatible with the reduction in the smallest pore components, noted above.



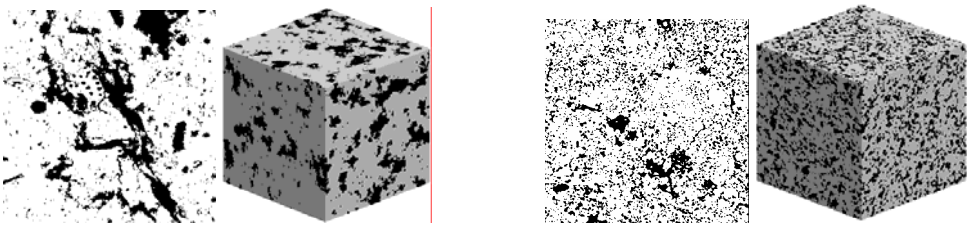
(a) (b)

Figure 3. Prediction of two-phase flow, (a) drainage and (b) imbibition curves for the original, the reconstructed and the self reconstructed images.

MULTI-SCALE RECONSTRUCTION AND 2-PHASE FLOW PREDICTION OF A CARBONATE ROCK

Here we also illustrate the use of the PAM approach to reconstruct multi-scale pore systems based on different-scale training images. We assemble a single multi-scale pore system by integrating the different-scale systems into a unified image. We then predict two-phase flow properties using the extracted network from this unified pore system. This approach can be applied to other scales.

We have two different scale 2D thin section images with a factor of ten difference in the pixel resolution i.e. 1.33 μm and 0.13 μm (Figure 4). These different scale images are used as input for the reconstruction of 3D carbonate macro- and micro-pore structures, as shown in Figure 4.



(a) (b) (c) (d)

Figure 4. Carbonate SEM images and reconstructions: (a) Coarse resolution image of 1.33 μm /pixel; (b) coarse-scale reconstruction with volume of 200^3 voxels; (c) fine resolution image 0.13 μm /pixel; (d) fine-scale reconstruction with volume of 500^3 voxels.

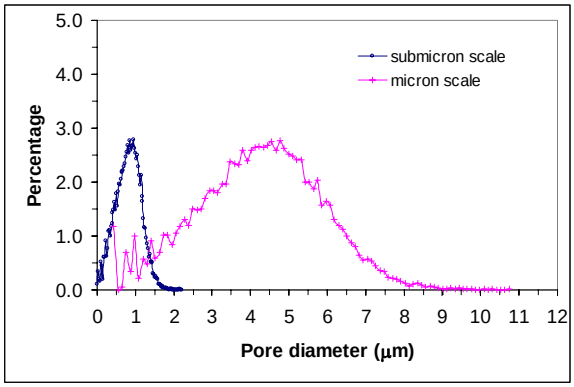


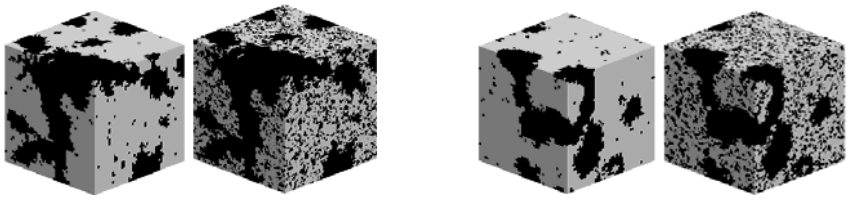
Figure 5. Pore size distributions in the reconstructed carbonate: Fig. 8b – coarse scale model - and Fig. 8d – fine scale model.

The resulting pore-size distributions (Figure 5) clearly show the effects associated with image resolution. The higher-resolution models (sub-micron scale PAM) indicate an average pore-size diameter of approximately 0.8 μm. In contrast, the coarse-resolution models (micron scale PAM) show a much larger mode for the pore size of about 4.5 μm. Using a low-order neighbourhood scheme, it is not possible to reproduce all scales simultaneously in the reconstruction.

However, it may be possible (see below) to combine the different-scale models to derive a better understanding of the composite material.

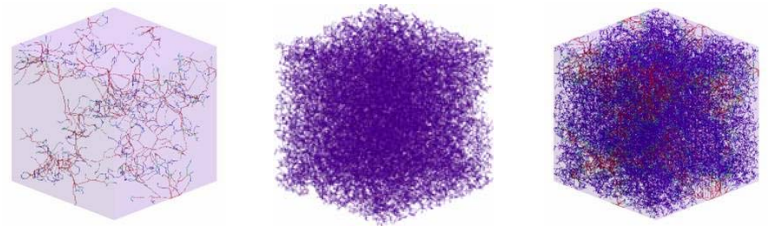
When the two different scale reconstructions are generated, as in Figure 4, these must be combined to give a single composite model. One possible approach is to refine the coarser scale 3D image to equivalent resolution as the finer scale and then combine these two structures with the same volume into a single model. For example, Figure 6a is a sub sample extracted from Figure 4b with volume 50^3 voxels, which has a resolution of 1.33 μm/voxel. We then (i) refine the image up to 500^3 voxels (dividing every voxel into a 10x10x10 sub-region) hence the refined image has a finer resolution of 0.13 μm/voxel, and then (ii) superimpose (for each voxel, it is assigned to be a pore if the corresponding voxel of either input image is a pore) the refined image on the fine-scale image of Figure 4d to form the integrated structure shown in Figure 6a′. The same procedure was applied to construct Figure 6b′.

Using the combined structure of Figure 6a′, we extract a new network (Figure 7c). This new pore structure has an average coordination number of 2.65, which is slightly higher than the 2.60 of the original coarse scale image. The maximum coordination number increased from 12 to 89. In addition, the permeability increased from 14 mD to 18 mD, since the poorly-connected macropores are now connected by micropores. Using the extracted networks, we can predict the two-phase flow properties (Figure 8) using our network flow model (Ryazanov et al. 2008).



(a) (a') (b) (b')

Figure 6. Illustration of the integration of the coarse and fine scale networks for 2 realisations of the multi-scale carbonate model. Figures show cases with only macroporosity (a, b) and with both macro- and micro-porosity (a′, b′).



(a) (b) (c)

Figure 7. Extracted pore network skeletons from (a) coarse scale, (b), fine scale and (c) the combined scale (c). (a) extracted network from Fig. 6a; average connection 2.6, maximum connection 21, permeability = 121 mD; (b) extracted fine scale network from Fig. 4d, average connection 2.55, maximum connection 16, permeability = 0.42 mD; (c) extracted fine scale network from Fig. 6 a, average connection 2.66 and maximum connection 89, permeability = 348 mD.

It can be seen that there are some differences between the curves for the coarse-scale and combined models showing that the presence of the microporosity does have an effect. In the self-reconstruction described above in this paper, we suggested that the loss of the smallest pore components resulted in a reduction of flow properties, and here we show that the inclusion of the small pores improves the flow. We are currently applying these techniques to a suite of carbonate samples, for which the flow data has been measured; this work will appear in due course. Additionally, we intend to apply the self-reconstruction validation to the multi scale cases in the future.

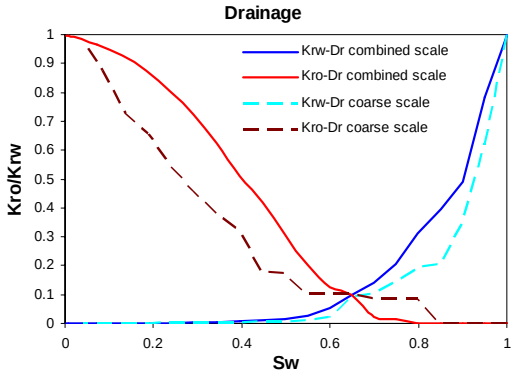


Figure 8. Two-phase flow predictions using a pore network flow model from coarse scale (dashed line) and combined scale (solid line).

SUMMARY AND CONCLUSIONS

In this work, we describe an approach for reconstructing and predicting multi-scale flow properties of homogeneous sandstones and inhomogeneous carbonates by first constructing a 3D pore image from 2D thin sections using the Pore Architecture Model approach (Wu et al., 2006, 2007). We then apply our pore analysis tools (PATs), which are a suite of algorithms which allow us to extract quantified descriptions from which we can build network models for simulating two- and three-phase fluid flow at the pore scale (Jiang et al., 2007).

In assessing the stability of the reconstruction method , we take as our starting point, a 3D CT image of sandstone as "reference" data. We then use "self-reconstruction" as a robust test of the methodology. The fact that (a) the PAM generated 3D image agrees in detail with the original "reference" image, and (ii) that successive "self reconstructions" agree reasonably well, validates the PAM approach in simple sandstone rocks, although there is the potential for improving our treatment of the smallest pore components.

The PAM technique has also been applied to a carbonate rock to tackle the problems associated with the fact that such rocks have a multi-scale pore system. We have separately constructed the 3D macro- and micro-pore system models at different (coarse and fine scales) resolution of the thin sections. These were then combined into the same unified model which incorporated both scales of pore heterogeneity, from which we extracted the corresponding multi-scale GT network which was used to calculate relative permeability.
A comparison between the calculated two-phase relative permeabilities of the macro-pore system and the combined macro/mico-pore system did show some differences. We do not fully explain these results here, or present any comparisons with experiment. Here, our main objective is to illustrate the methodology and approach, and to demonstrate the feasibility of calculating two-phase properties in such multi-scale pore systems. This approach is being applied to carbonate rocks with experimental property data, and the next step of this work will investigate the self reconstruction validation and compare the flow properties predicted using PAMs with lab experiments.

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