Texture-Based Classification Approach to Simulate Absolute Permeability in Reservoir Rock Sample

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Abstract—Carbonate reservoirs represent around half hydrocarbon reserves in the world. However, characterizing rock properties in these reservoirs is highly challenging because of rock heterogeneities revealed at several length scales. In the last two decades, a new approach known as Digital Rock Physics (DRP) revealed high potential to better understand rock properties behaviour at pore scale. This approach uses 3D X-ray Micro tomography images to characterize pore network and also simulate rock properties from these images. Even though, DRP is able to predict realistic rock properties results in sandstone reservoirs it is still suffering from a lack of clear workflow in carbonate rocks. The main challenge is the integration of properties simulated at different scales in order to obtain the effective rock property of core plugs. In this paper, we propose to characterize absolute permeability in a carbonate core plug sample using texture analysis. We propose to segment 3D micro-CT image in terms of textures and predict the overall rock permeability by integrating classification result with absolute permeability simulations values computed locally for each texture class. Finally, we discuss and compare our numerical simulation results with experimental measurement from the laboratory.

Keywords—Permeability, Texture, Micro-Computed Tomography, Classification

I. Introduction

Characterizing porosity and absolute permeability in cored area from oilfield reservoirs is a crucial step to evaluate hydrocarbon reserves. This characterization is more challenging in carbonates representing half of the world reservoirs. Indeed, their high heterogeneity due to presence of pores at macro, micro and nano scales makes properties characterization very complex [1]. Recent development in image acquisition techniques based on X-ray Micro-tomography, Focused Ion Beam (FIB) and Scanning Electron Microscopy (SEM) allow investigating core samples at very high resolution and simulating rock properties at pore scale [2, 3, 4]. This approach known as Digital Rock Physics (DRP) is seen as a complimentary tool to conventional laboratory measurements [5, 6, 7, 8, 9, 10].

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Nevertheless due to physical limitations of detectors size in scanning devices it is not possible to image macro, micro and nano pores at the same scale. Indeed, the best resolution to scan a core plug sample of 1.5 inches diameter using X-ray micro tomography with a detector size of 2000x2000 pixels is 20μm. At this scale, usually, macro pores and main textural heterogeneities can be visualised. In order, to image smaller pores, subsets of few millimetres are extracted physically and scanned at higher resolution around 1 to 2 μm.

We introduce an approach using texture modelling in order to estimate porosity and permeability of some carbonate rock samples. This approach aims to discriminate objectively spatial variability of textures in Micro CT images. The main assumption is that variability in textures is related to variability in porosity and permeability [11, 12]. The idea of using X-Ray micro-CT scan images to estimate rock properties and textural facies classes of core samples has physical bases. Indeed, the perceptual texture of these images reveals granularity, mineralogy and porosity features. Relationships between texture and granularity have already been carried out in the field of electrical borehole images [13, 14, 15]. Prasad and Mukerji implemented textural statistical models in scanning acoustic microscope images of shale microstructures in order to establish relationships with effective elastic properties [16]. Knackstedt et al used textures to model rock fabrics from digital 3D images and used it as a quantitative analysis tool of anisotropy in grain orientations [17]. More recently, Jouini and Keskes implemented a parametric model of textures to find main representative textures from X-Ray Computed tomography core samples images in sandstones and predict rock properties [12].

In this study we discretize, first, X-Ray Micro CT images into a regular grid. Then, we use a textural parametric model to classify each cell of the grid using supervised classification. The main parameters are first and second order statistics such as mean, variance, range and autocorrelations computed from sub-bands obtained after wavelet decomposition. Furthermore, we fill permeability property in each cell using two strategies based on numerical simulation values obtained locally on subsets through Lattice Boltzmann Method [6,18, 19, 20]. Finally, we simulate numerically the effective permeability using Darcy's law simulator.

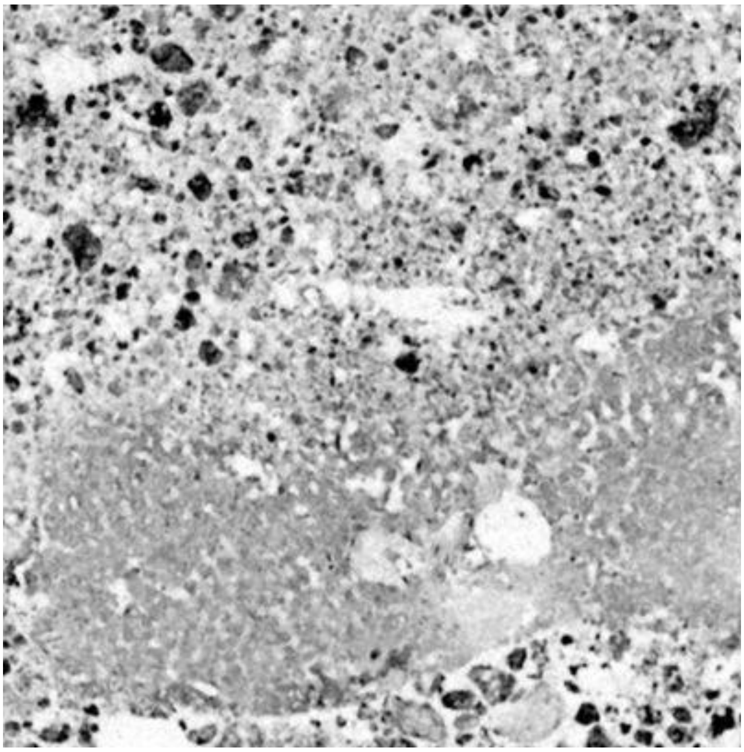

Fig. 1. 2D slice (2000x2000) grey level image extracted from 3d X-Ray Micro-Computed tomography image of carbonate sample revealing several textures. (Resolution 3µm)

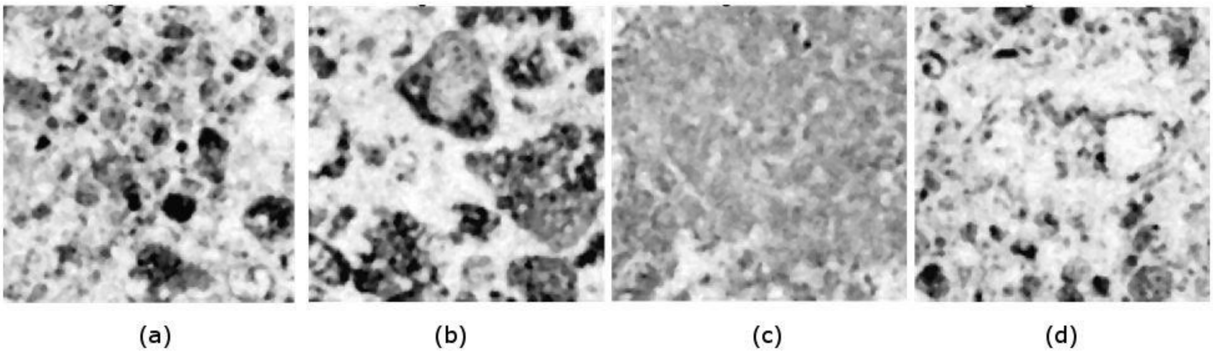

Fig. 2. Four classes of textures identified from the original image sample.

Class Texture	T1	T2	T3	T4
Sample 1	1	2	3	4
Sample 2	1	2	3	1
Sample 3	1	1	3	1
Sample 4	1	2	3	4
Sample 5	4	2	3	4
Sample 6	1	2	3	4
Sample 7	1	2	3	4
Sample 8	4	2	3	4
Sample 9	4	2	3	4
Sample 10	1	2	3	4
Classification rate	70%	90%	100%	80%

Table 1: Rate of good classification for 40 samples from 4 type of textures

II. METHODOLOGY

A. Rock sample images

X-ray Micro-tomography scanners generate after acquisition and reconstruction 3D grey level images where voxels values depend on material density. High values corresponding to bright voxels are related to solid phase whereas dark ones denote pores. Due to high variability of textures in samples it is very difficult to implement a unique segmentation method to separate solid and void phases. In this study, the data consists of 3.8 centimetres diameter carbonate sample from United Arab Emirates oilfield reservoir. First, we image the full sample at a resolution of 20µm. At this scale, the acquired image is homogenous which means all pores are below image resolution so we have extracted a smaller subset of 6 mm3 and scan it at 3µm resolution. At this scale part of pore network starts to be revealed and we observe a variability of textures in the subset. Fig. 1 shows presence of several textures related mainly to variability of pores sizes and their distribution in space. The standard DRP approach is based on segmenting the 3D image and simulate absolute permeability on extracted pore network. Nevertheless, on most of carbonates samples this procedure can hardly be implemented due to limitation of image acquisition system to capture connectivity between pores. In the literature several segmentation algorithms were implemented for grey level images. Techniques implemented are based mainly on semi-automatic or fully automatic approaches [21, 22, 23]. The main advantage of automatic methods is to eliminate operator subjectivity. In our study, we implemented mainly Bi-level segmentation algorithm for the segmentation process. However, extracted pore networks from 3D images at fine scales (13µm and 5µm) reveal very limited connectivity called also absence of percolation between opposite faces. Indeed, we apply a connected components algorithm into resolved pore phase and find that connected porosity proportion is very low. Whereas, experimental measurements show that permeability values for samples is in the range of few milli Darcy. This observation reveals that most of pore connections are below image resolution. Thus, it is not possible to run directly a simulation of fluid flow into unconnected pore network. However, we observe that connected component techniques reveals local connectivity for several sub-cubes into the same image. We propose to discretize each acquired 3D X-ray Micro tomography image in to a regular grid where pore networks percolate locally. In other words, we segment each subset of the grid to be able to run numerical simulations of permeability. Also, we observe that segmentation process depends mainly on the texture of subsets so we discretize 3D image into a grid by classifying each subset of the grid using texture classification.

B. Texture model and classification

In the literature, there is no universal definition for texture but several approaches exist depending on applications [24, 25]. Parametric modelling consider a texture as random variable governed by a set of descriptors such as contrast, correlation, directivity, uniformity, entropy [26,27]. In our study, we implement a parametric model using mainly first and second order moments obtained after decomposing texture into steerable pyramids [28]. For example, if we choose decomposition with 2 scales, 3 orientations, and autocorrelation window of 7 the total number of descriptors will be 185 parameters for a texture. The model was implemented in several applications such as texture synthesis, texture analysis and image classification [15, 29, 30]. We select the main representative classes by inspecting visually texture of rock samples. Fig.2 shows some examples of main representative classes. We propose to validate the texture model computing the rate of good classification. We created a small database of classes from the original 3D digital image containing 10 samples each. Then we classified all images by finding the minimum distance between each vector representing the image texture and the reference class. Table 1 summarizes classification results for the sample textures illustrated in Fig. 2 and the overall average of good classification obtained was 85%.

Based on these results, we implemented the texture classification on the whole digital image. First, we divide the 3D digital image into a regular grid of cells. Then, we analyse each 2D image of the cell and classify it using the proposed parametric model. Finally, we select the mode of the resulted classifications into each cell as representative class.

C. Absolute permeability simulation

After modelling and classifying subsets the absolute permeability is estimated by using Darcy's law, which assumes a linear relation between gradient of pressure and volume of flow per unit area, to compute absolute permeability based on (1).

$$K=(\mu LQ)/(A\Delta P) \tag{1}$$

where K is the absolute permeability, Q is the average velocity of particles called also flux from LBM simulation, ΔP is gradient of pressure along a sample of length L, μ is the fluid viscosity and A is the surface area of the sample cross section. In order to have reliable and representative values we run simulations into several subsets with same texture to obtain a distribution of permeability values inside each class. Finally, we populate the 3D grid of classified textures with local permeability values from each distribution and we estimate the effective permeability of the image sample using Darcy's law simulation and averaging techniques.

III. Results and discussion

Fig. 3 shows four groups of dataset points coloured based on texture classification result. Texture 1 dataset reveals a range of porosity between 11% and 17% with permeability range between 0.01mD to 14mD. Figure 2.a illustrates image Texture 1 which reveals highly porous subset with medium size pores when compared to texture2. Texture 2 reveals higher porosity and permeability ranges of respectively 16%-19% and 0.9mD-110mD. This is expected as this texture shows larger pores with high connectivity. Also for both Texture 1 and Texture 2 show a linear relationship. Texture 3 shows very low porosity and permeability data points because of the low number of pores and their low connectivity. Finally, texture 4 reveals a large proportion of small connected pores with a range of permeability between 0.01mD to 2mD.

Even though, the porosity-permeability cross plot along with textural information allow identifying classes with similar behaviour, there exists an overlap between these groups. In order to simulate the effective absolute property, we fill the classified grid with random values coming from the ranges in Table 2. Then, we simulate several realizations using the Darcy simulator.

Fig.4b shows the simulation result for one realization and the effective property obtained is Keff=0.696 mD. The range of variation for the effective property is in the interval [0.65, 0.86] in mD for all realizations. This result shows the stability of prediction and the relevance of using textural information to model permeability property.

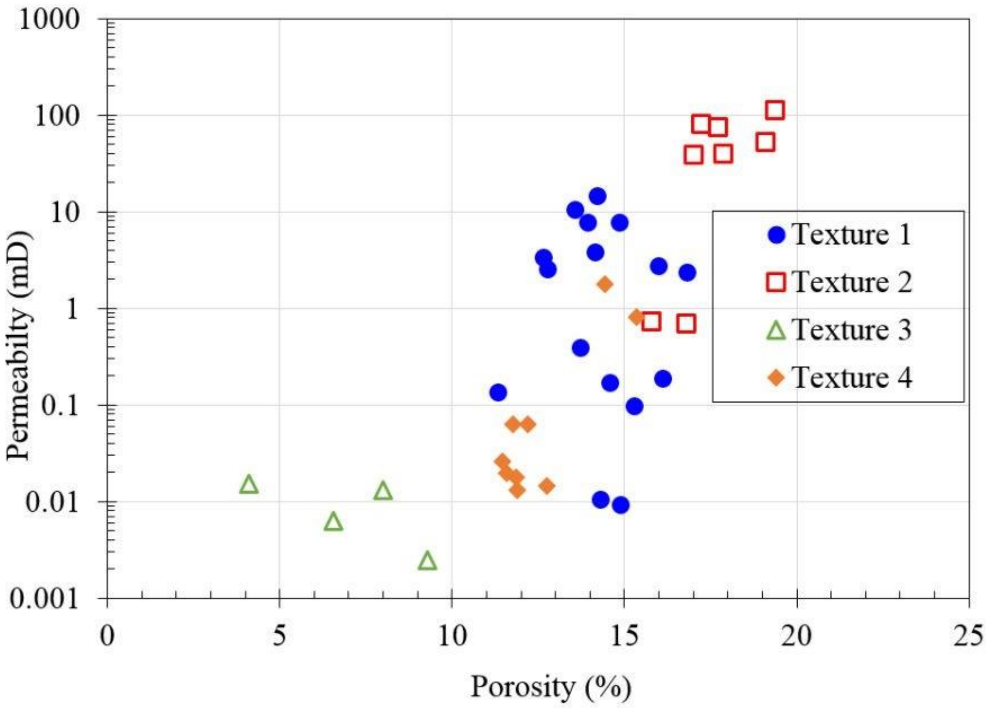

Fig.3. Relationship between Porosity-Permeability cross plot and textural analysis

K	T1	T2	T3	T4
min	0.009113	0.7	0	0.013194
max	14.642	111.4	0.0154	1.78

Table 2. Permeability ranges for main four textural classes

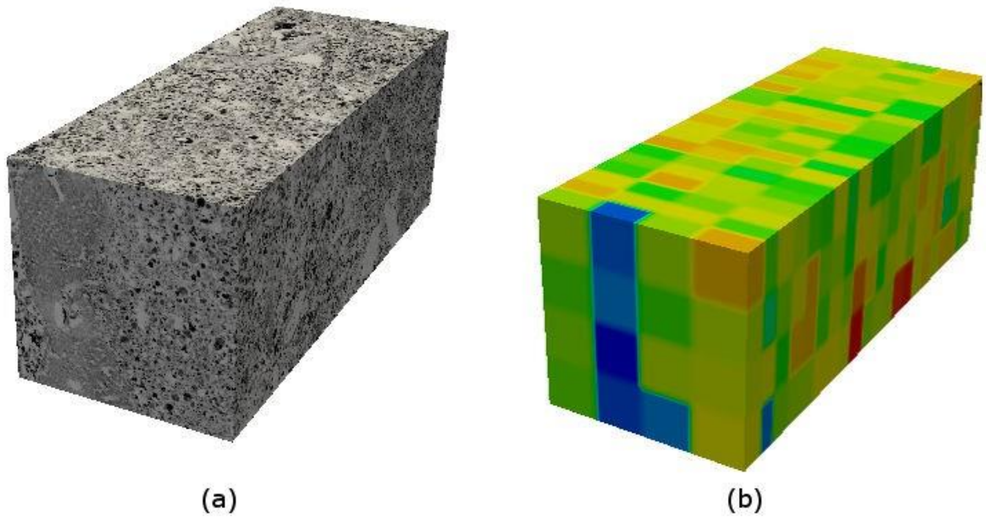

Fig. 4. a) Original 3D X-ray Microcomputed Tomography image. b) Permeability grid filled with local permeability simulation results.

IV. Conclusion

The laboratory measurement of the experimental absolute permeability for the 3.8 cm diameter core plug sample gave a value of 1.2 mD. Numerical simulations obtained from the different approaches were carried on a selected subsample of the whole core plug. Simulated result is in the same range than the experimental one for all approaches. Indeed, homogeneity visualized at core plug sample scale scanned at 20μm can explain the representatively of the subsample selected. Heterogeneity in this sample appeared only at pore scale and our strategy based on texture was able to capture this variability and integrate it to obtain a relevant absolute permeability prediction. The main advantage of the proposed approach is to introduce an objective assessment of texture variability which is physically related to the porosity and permeability properties. However, the main limitation is the selection of textures representative into the sample done visually. We are working to improve this process and make it more objective by using non-supervised classification techniques to find most representative textures automatically. Also, we are working on proposing a new 3D parametric model for textures to better represent textures and improve simulation results for rock properties.

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