Fuel 217 (2018) 218–225

Contents lists available at ScienceDirect

Fuel

journal homepage: www.elsevier.com/locate/fuel

Full Length Article

Nanoscale and multiresolution models for shale samples

Pejman Tahmasebi

Department of Petroleum Engineering, University of Wyoming, Laramie 82071, USA

ARTICLE INFO

Keywords:
Nano-size
Integration
Shale modeling
Micro-model
FIB-SEM

ABSTRACT

Characterization of shale systems requires imaging at different scales. One reason can be due to a diverse pore-size distribution. Low-resolution images often cover the large-scale structures and are available for a large region of the sample. On the other hand, fine-scale images usually cover a small region and they are mostly used to discover the complexity within the nano-scale pores in shale samples. Acquiring large image containing both the micro- and the nano-scale feature can be very expensive and time demanding. In this paper, a new method for integrating of such images at different scales is proposed. The aim is to include the nano-scale information within the coarse images. The input of this method is a set of coarse- and fine-scale images. The corresponding regions of each fine-scale image within the coarser image are determined using a similarity map. Then, the coarse image is refined iteratively to include the fine-scale information. The final image contains both the micro and nano-meter images and can readily be used for various purposes.

1. Introduction

Unconventional reservoirs, in particular, shale systems, play an important role in the current and future of global energy resources. Characterization of such reservoirs, however, are tied up with several new complexities. For example, shale samples contain multimodal pore-sizes, demanding the presence computational techniques a major revisiting and development. Pore-size distribution in shales, maybe, is one of the key characteristics that extricate such formations from the conventional reservoirs [1,2].

Digital images are a common way to represent the inherent complexity in the unconventional reservoirs. Such images are characterized by their resolutions. The need for using high-resolution images due to including more physics in modeling is increasing. Based on the recent high-resolution scanning electron microscopy (SEM) studies, it has been shown that pores are dominated elements, including, inter-particle, organic-matter pores, interparticle mineral pores and intra-particle mineral pores, which the sizes vary from order of micrometer (e.g. inter-particle pores) to a few nanometers (e.g. 2–100 nm in intra-particle pores); see Fig. 1 [3–8]. Various types of pores, and their corresponding modeling, have been identified during the last several years [1,3,5,9–21].

Studying the above-mentioned pore types requires using focused ion beam-scanning electron (FIB-SEM) [22,23] This imaging tool provides high-quality images of the discussed pores, but its application is limited to small samples and its 3D application still requires future research and progresses. Aside from capturing only a small region using the FIB-SEM, providing several of these images for accurate characterization of shale samples is not economic. Nonetheless, using the FIB-SEM images is inevitable for evaluating the permeability and other petrophysical properties [24–29].

On the other hand, low-resolution images, such as the ones are generated by microtomography (e.g. X-ray), can cover larger samples while they often miss the small pores. Thus, various images with different resolutions are usually taken with this hope that the overall structures are detected. For example, Okabe and Blunt [30] used two images at different scales. The low-resolution 3D X-ray image is considered as a basis and the small-scale pores shown in the 2D SEM image was reconstructed stochastically and the results are combined wherein both the small- and large-scale information can be observed. In this method, producing stochastic models is only restricted to small-scale features. Thus, one may not capture the possible variabilities for the larger pores. Other related methods have merged images from different scales using superimposing and pore-networks [31–37]. Later, Tahmasebi et al. [6,38–40] used 2D images from two different resolutions and integrated them in a 3D stochastic framework. They separately built the nano – and micro-scale models and superimposed the models to make a 3D image with the presence of both nano- and micro-pores. It is worth mentioning that these two methods perform 2D-to-3D reconstruction since the SEM images are available in 2D.

As an alternative, one can provide very large SEM images and produce several other possible scenarios for pore-size distributions. However, this requires an intensive image with a size of around 30,000 × 30,000 pixels, which is not feasible. Thus, as discussed, the

E-mail address: ptahmase@uwyo.edu.

https://doi.org/10.1016/j.fuel.2017.12.107
Received 16 October 2017; Received in revised form 12 December 2017; Accepted 22 December 2017
0016-2361/

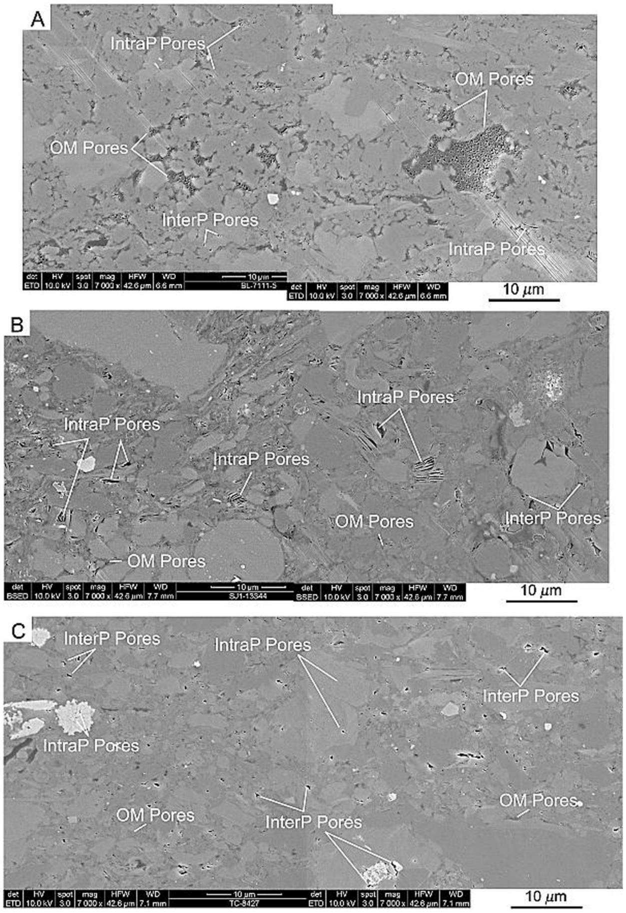

Fig. 1. Demonstrating various pore types in shale reservoirs. A) organic-rich sample wherein the OM pores are dominated, B) Siliceous calcareous – dominated interapore, C) Siliceous calcareous - dominated interpore [3].

limitation in terms of the size of the image always exist and the available shale images only explain the heterogeneity for a small region. Therefore, the pores smaller than the resolution of the image and, likewise, the ones larger than the size of the image are always missed. Such a shortcoming can severely change the designated plan for shale developments as these samples manifest a very wide range of pore sizes. This paper aims to address this existing deficit by presenting a method for producing large and high-resolution samples using small images from different scales. Indeed, the primary goal in this paper is to use only a limited number of images (e.g. 7–8) at different scales with small sizes (e.g. 200 × 200) and produce high-resolution realizations. By doing so, thus, one does not require to provide very large and high-quality images. Finally, the trade-off between the size of the image and spatial resolution needs to be considered for the complex shale samples. Thus, one requires doing either upsampling or downsampling for acquiring the data at different scales.

The primary motivation in this paper is depicted in Fig. 2. The low-resolution images ($S = 0$) are usually available. For the sake of demonstration, we assume that high-resolution SEM images of the same region, in two higher resolutions, are also presented, namely, $S = 1$ and $S = 2$. As can be seen, the middle resolution image (i.e. $S = 1$) can reveal some of the structures, while the finest resolution, that is $S = 2$, can show the nano-pores. Due to the earlier discussed issues, these images are often not available in the same sizes. In this paper, a different approach is designed by which one can start with a low-resolution image ($S = 0$) and efficiently take advantage of the other available high-resolutions images by refining the coarse image. The novelty of this method lies on the fact that one does not need to provide large images at various scales, but only small images with resolutions can be used to enrich the initial large image.

2. Methodology

As mentioned, the current techniques only work with one (single-resolution) or two large images (nano- and micro-scale). In this paper, however, several small images are used to build high-resolution models that contain the information at both small- and large-scale. To this end, assume a few small images (e.g. 200 × 200) at different resolutions are available. Some of them are shown in Fig. 2. Clearly, the high-resolution images only cover a very small region of the original low-resolution image in the middle. The same scenario is valid for the other higher-resolution image with a larger coverage.

Before describing the algorithm, it should be noted that the source images are signified by $S^L[\xi] = \{S^0[\xi],S^1[\xi],...,S^{L-1}[\xi],S^L[\xi]\}$. In this study, three level of images, namely $L \in [0 \quad 2]$, are used. Each of these levels has their own resolution, indicated by $R \in [1 \quad 3]$. Further, ξ indicates the image number in each level. Thus, S_R^L represents the image at level L and resolution R. That being said, the proposed algorithm first upsamples the coarsest image S_1^0 to reach the resolution of the next available higher resolution, namely S_2^0 using the bi-cubic interpolation method (Section 2.1). The resulted image will have the same number of pixels as the ones in $L = 1$. Such a bank of images, $S_R^L = \{S_1^0,S_2^0,...,S_{R-1}^L,S_R^L\}$, can be generated before the modeling begins. Then, the similarity of the upsampled image S_2^0 is calculated across all the available images in $L = 1$ (Section 2.2). The aim of this step is to quantify the similarity of the middle level images with the upsampled image. In fact, one requires identifying the appropriate finer images for each region in the coarse image, as each of them correspond to a specific part. After constructing the similarity map between S_2^0 and S_1^1, the most similar image(s) for each part of S_2^0 is identified, by which the algorithm only considers the selected images for the refining process. The refining step is conducted by using the hybrid pattern- and pixel-based simulation (HYPPS) (Section 2.3). It is worth mentioning that one can freeze some parts in the coarse image if they do not contain artifact. In fact, aside from being low resolution, these images sometimes can detect specific minerals and regions much better than other parts. Thus, one may prefer to keep those regions in the refinement process until a certain level. After completing this step, a new higher-resolution image $\mathbf{O}_R^l$, based on the patterns in $l = L{-}1$, is generated that contains the fine-scale information. Similar to the previous step, O_1^1 is upsampled to produce the so-called high-resolution image to be used with the images in $L = 2$. Alike the described procedure, the similarity between $\mathbf{O}_1^1$ and images in $L = 2$ is quantified. Then, the available images are used based on their regional similarity accordingly to refine the input image $\mathbf{O}_1^1$. The output image demonstrates a large image with the same resolution observed in $L = 2$. The proposed algorithm is graphically depicted in Fig. 3.

2.1. Upsampling

Since the base images from the previous scales are required to be refined with the next finer ones, thus, they need to be first upsampled. In this study, we used bi-cubic interpolation method, which results in an accurate interpolation. This method can preserve the structures without producing too many artifacts. This method supposes the function values f and its derivatives f_x, f_y and f_{xy} are known at four corners of a unit square, namely (0, 0), (1, 1), (1, 0) and (0, 1). Then, the interpolation surface can be obtained by:

$$s(x,y) = \sum_{i=0}^{3} \sum_{j=0}^{3} a_{ij}x^i y^j \tag{1}$$

Solving this equation requires determining 16 coefficients a_{ij} [41,42].