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A case study on homogeneous and heterogeneous reservoir porous media reconstruction by using generative adversarial networks

Siyan Liu[a,*], Zhi Zhong[b], Ali Takbiri-Borujeni[c]
Mohammad Kazemi[d], Qinwen Fu[a], Yuhao Yang[a]

[a]*The University of Kansas, Department of Chemical & Petroleum Engineering, Lawrence, Kansas, USA, 66045*
[b]*Bureau of Economic Geology, The University of Texas at Austin, Texas, USA, 78713*
[c]*West Virginia University, Department of Petroleum and Natural Gas Engineering*
[d]*Slippery Rock University, Department of Petroleum and Natural Gas Engineering*

Abstract

The advancing of modern X-ray computer tomography technology provides a powerful tool for us to illustrate the details inside the reservoir rock in three-dimensional space. Pore-scale rock characterization, modeling, and related fluid flow simulation can be challenging due to the high complexity of various rock samples. Conventional pore scale structure modeling methods such as various stochastic methods were developed for reservoir rock 3D microscopic structure reconstruction in order to generate representative realizations for numerical simulations and property upscaling approaches. In this work, generative adversarial networks (GANs) is used for generating the synthetic micro representations of porous rock by acquiring non-linear statistical information from the real 3D rock images in an unsupervised learning scheme. The related 3D image pre-processing, network training and adjusting as well as data post-processing procedures are addressed. The network prediction results from a homogeneous Berea sandstone and a heterogeneous Estaillades carbonate demonstrated the capability of GANs for high-resolution porous rock image representations reconstruction, generated and real images are compared via various visualizations and inspections. The study also illustrated the importance of the training image preprocessing, which indicating the data augmentation techniques can be one of the promising improvements in terms of capturing the sparsely distributed features from heterogenous 3D images and reconstructing the synthetic realizations, meanwhile, the robustness of the model during training process is enhanced when limited real data is available.

* Corresponding author. Tel.: +1-(785)330-3163
E-mail address: liusiyan@ku.edu

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1. Introduction

Modeling and simulating porous media materials or rocks from pore-scale perspectives are substantial topics in various science and engineering field such as hydrology, material science, environmental engineering and petroleum engineering[1]. One of the powerful tools for revealing the micro-scale properties of the porous media is Micro-CT imaging technique which generates high-resolution three-dimensional images for microscopic structure reconstruction, thereafter the analytical and numerical studies can be conducted within the 3D realizations in terms of geometrical, morphological statistical analysis. Conventional grid-based computational fluid dynamics methods need huge amount of grid blocks to discretize the computation domain, also the local grid block refinements are necessary in order to capture the properties in smaller scale due to the heterogeneity which requires even more grids for reducing the calculation uncertainties Even equipped with modern massive paralleled computer system, the number of degree of freedoms are several orders of magnitude greater than the actual number of unknowns we can handle effectively, also the highly heterogenous geometrical domain coupled with Multiphysics phenomenon can causes convergence failure during numerical simulations. Pore network based upscaling techniques aimed at reduce the oversimplification and enhance the representations of pore network by applying coarse-scale discretization for void space[2]. In addition to pore network extraction and simplified fluid flow simulations, stochastic reconstruction of the pore scale to larger scale structure models are developed in order to generate synthetic realizations which respect the geometrical statistical distribution from the real samples[3].Unlike the various conventional stochastic 3D structure reconstruction techniques such as two-points, MPS methods[4]. Generative adversarial networks (GANs) is a type of delicate artificial neural network developed by Goodfellow [5] which contains a pair of neural networks working together during the training and predicting process, one of them called 'generator' G(z) which will evolve itself during training process to generate data from input noise variables pz(z), and another one called 'discriminator' D(x) which represents probability that the generated data x belongs to real data, they will be trained simultaneously to enhance the discriminability of D and maximize the probability of G to generate realizations. The network D and G itself can be either Multi-layer perceptron (MLP) network or convolutional neural networks (CNNs)[5]. The training process can be analog to a 'min-max game' between two players based on the value function V(G, D):[5]

$$\min_{G} \max_{D} V(D,G) = E_{x \sim p_{data}(x)}[\log D(x)] + E_{z \sim p_z(z)}[\log(1 - D(G(z)))] \tag{1}$$

The nature of the unstable running mechanisms leads to the highly unstable training process, therefore, improved GANs are proposed to enhance the training stabilities in order to suit for multiple purposes[6]–[8]. Instead of applying GANs for 2D image reconstructions[5], there are some works proposed to reconstruct 3D images and objects[9]. Lukas et al., 2017 applied GANs to reconstruct the 3D realizations from Micro-CT images and evaluated the capabilities of learning pore-scale representations and microscopic properties from real images[10]. We constructed our GANs and demonstrated the training and realizations reconstructions from different rock Micro-CT images, also illustrated the impact of improved pre-processing and post-processing especially when dealing with the heterogeneous porous medium.

2. Methodology and experimental

2.1. Experimental data preprocessing

The experimental data used in this study are two segmented 3D Micro-CT scanner images, which means the 3D images are three-dimensional binary data that can be easily converted to arrays with Cartesian coordinates and segmented labels. The label within each one of the space coordinates is either zero or one, which represents void space or rock matrix respectively. In this study, 'Berea sandstone'[11] and 'Estaillades carbonate'[12] are downloaded from the website of Petroleum Engineering & Rock Mechanics Group, Department of Earth Science and Engineering, Imperial College.

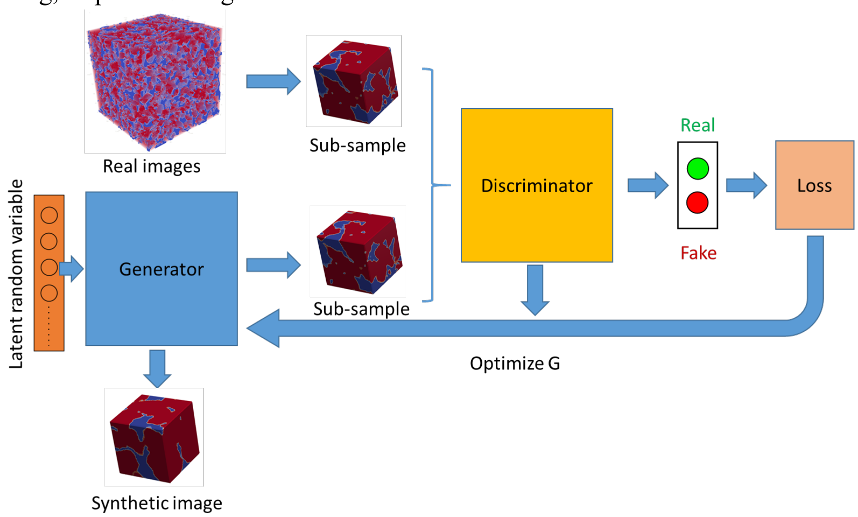

Figure 1 Workflow of applying GANs in 3D image reconstruction (modified from Deep Learning for Computer Vision: Generative models and adversarial training (UPC 2016))

The former sample is very homogeneous fluvial sandstone in terms of grain size and shape, and the latter sample shows high heterogeneities in grain, pore size and shape distributions. Image from Berea sandstone contains 400^3 voxels and the image resolution is 5.345μm, Estaillades carbonate image has a larger size (1000^3 voxels) with 3.0035μm resolution. Due to the limitation of the image size as well as the computation resources, we use the method proposed by Lukas et al.[10] to extract sub-volumes of the original 3D image through a smaller size 'moving cube sampler', in order to extract sufficient representative training images, the moving strides are smaller than the size of sub-volume which means the sub-samples can overlap each other for generating more sub-samples. In the case of Berea sandstone image, the sub sample with 64^3 is big enough for capturing the pore, grain geometrical properties and the interactions among grains (Figure 2.a), but 64^3 sampling size is far less than favorable representative sub-volume due to the highly heterogeneous microscopic structure within Estaillades carbonate image, even after the optimization of our training strategy that eventually we are able to fit the sub-volume of size 128^3 into memory, it is still not properly reflect the geometrical properties (Figure 2.b). To tackle this issue, we tried several down sampling approaches to reduce the size of the original 3D image while preserving the geometrical properties as much as possible, as the results, the original 1000^3 images are reduced to 512^3 and we are using 128^3 as the sub-sampling size for Estaillades carbonate image (Figure 2.c).

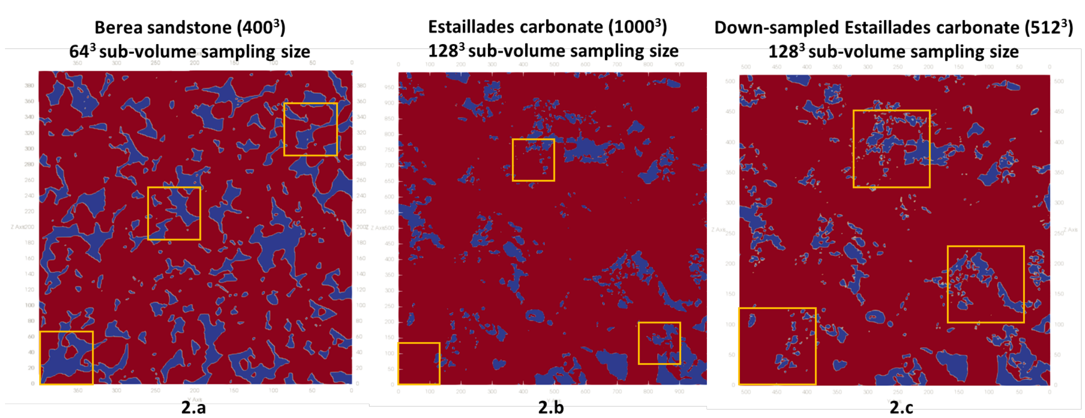

Figure 2 Shows the sub-sampling strategies for the two rock samples. 2.a shows the 64^3 sub-volume size is sufficient to include the pore, grain geometrical properties, and interactions; 2.b shows the initially tested 128^3 volume size is not able to capture enough information for training; 2.c depicts the solution for sub-sampling with 128^3 volume size in a down-sampled 512^3 for Estaillades carbonate sample

Ideally, the deep neural network can approximate any non-linear functions or non-linear problems as far as the network is well trained with representative training data set. Through visual inspections from the sub-volumes of Estaillades images, we found that part of the images contains sufficient information of the properties, but a lot of them contain much less representative structures due to the sparsely distributed pore-grain sizes and interactions. To solve this problem, we extended the 2D data augmentation techniques[13] to our 3D sub-sampling process by regularly or arbitrarily rotating the image (Figure 3a, 3b), therefore, a significant number of enhanced images are acquired for improving the robustness of the system.

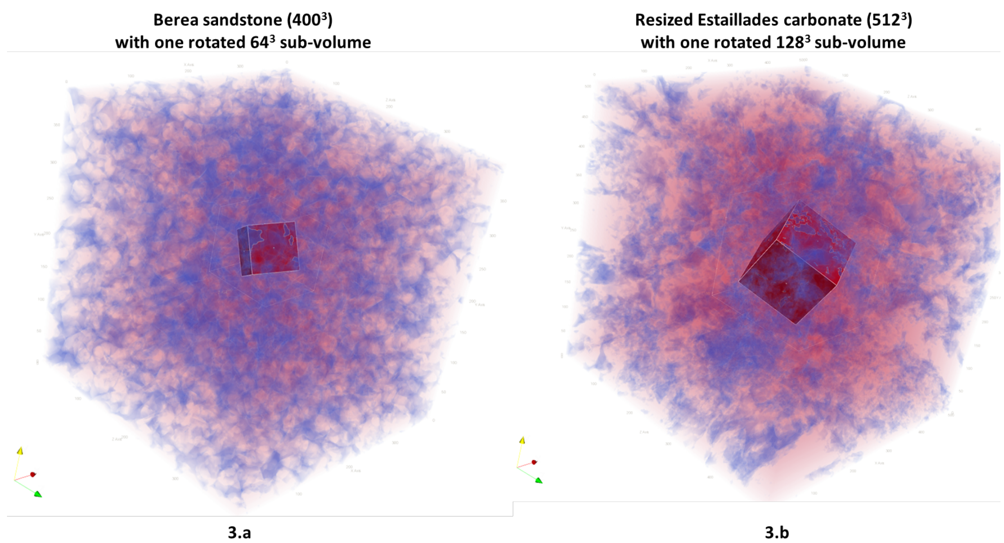

Figure 3 Illustrate the data augmentation pre-processes. 3.a shows a rotated 64^3 sub-sample in the original 400^3 Berea sandstone image; 3.b shows a rotated 128^3 sub-sample in the resized 512^3 Estaillades carbonate image.

2.2. Neural Network configurations and training

Our customized generative adversarial networks (GANs) are modified from the prevailing network structure Deep Convolutional Generative Adversarial Networks (DCGAN)[6]. During the training processes, the discriminator is trained from the real images and serve as a 'judge' to determine whether the generated realizations from the generator are correct or not with loss indications. Various hyper-parameters such as input size, filter size, layers, activation functions, optimizers, learning rates are fixed or dynamically tuned based on the performance of the networks, training stabilities as well as the manual inspection of the final outputs. The training was performed on a desktop computer with a single NVIDIA GTX 1080TI GPU, so it is important to find the optimum training strategy for different case scenarios due to the limited computation power and memory available.

2.3. Neural Network output and post-processing

The trained GAN models are capable of generating different size of realizations based on the image size input to the generator. Since the network learned the stochastic representations of the microscopic structure properties, then re-generating much larger size of 3D images are applicable, also the reconstruction of realizations is extremely fast compared to training processes, the only limitation again is the GPU memory limitation since the memory and storing space for 3D images are dramatically increasing with the linearly increasing image size or length. The maximum size the image we tested on our desktop computer is 528^3. Appropriate post-processing is necessary for image reconstructions. The networks can hardly be trained perfectly for certain case scenario, also due to the various level of complexity within different cases, the networks can be less trained or overtrained, as the results, de-noising processes and image enhancement techniques such as median filters are used, especially the results from Estaillades carbonate. The networks generated images are examined during the training process, and the final results are evaluated through 2D and 3D visualizations and comparisons.

3. Results

After various testing and optimization of the workflow including preprocessing, training and post-processing strategies, we obtained the results showing the 3D image reconstruction capabilities of GANs. Our input data is the sub-volume images sampled from the original 3D image through rotating augmentation approach. Size of sub-samples for Berea sandstone and Estaillades carbonate are 64^3 and 128^3 respectively. During the training, the network will periodically store checkpoints with necessary training status information and the instance for current status generator and discriminator. A semi-auto script is assisting us to do the manual visual inspection for the generated realizations from the generator. Figure 4 shows the generated images from the generator in different training stages, more training iterations is not necessarily producing better results, but it is good to try a longer training test in most cases.

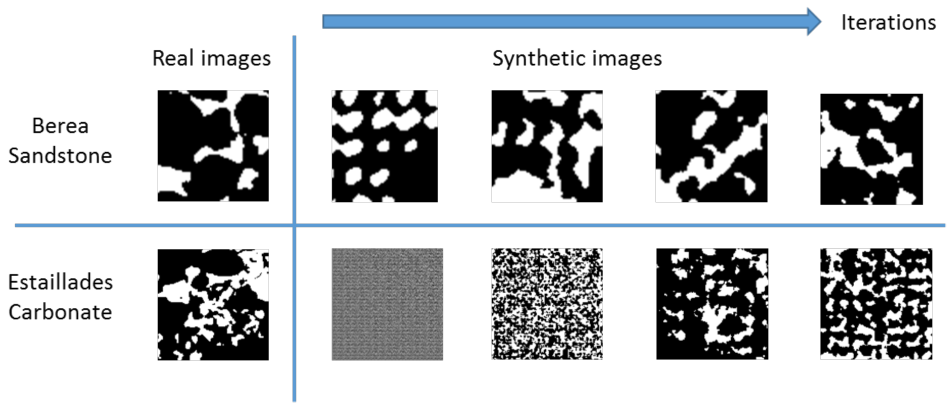

Figure 4. The real images and the images generated by the generator during training process for Berea sandstone sample and Estaillades carbonate sample

After a long period of training time when the loss of generator, discriminator is stabilized, also when the quality of the synthetic images tends to be stable. The generator status from last several iterations or the ones showing best performance through manual inspection is used for image reconstruction in different sizes. Figure 5 shows the 3D visualizations of image comparison between real rock scanned image and GANs synthetic image. We also tested the training process from the input data with or without data augmentation preprocess, the training for Berea sandstone became stable after around 3,000 generator iterations instead of more than 10,000 iterations in our previous experiments without data augmentations. In the Estaillades carbonate case, before augmentation we can hardly train the GANs to produce the meaningless images after proper post-processing, with data augmentation, our generator can produce some images that are somewhat showing heterogeneities in small scale. But as we can see the 3D view and 3D slicing view for real Estaillades carbonate and synthetic images, the generated 3D image is not very representative in the whole original image scale, it seems that the network learned the features from the smaller scale which comes from the 128^3 size of sub-volume samples. Due to the computation memory limitation, it is hard to increase the sub-volume size for obtaining more representative training data, but by using properly designed preprocessing workflow tends to improve the feature learning capability of the networks.

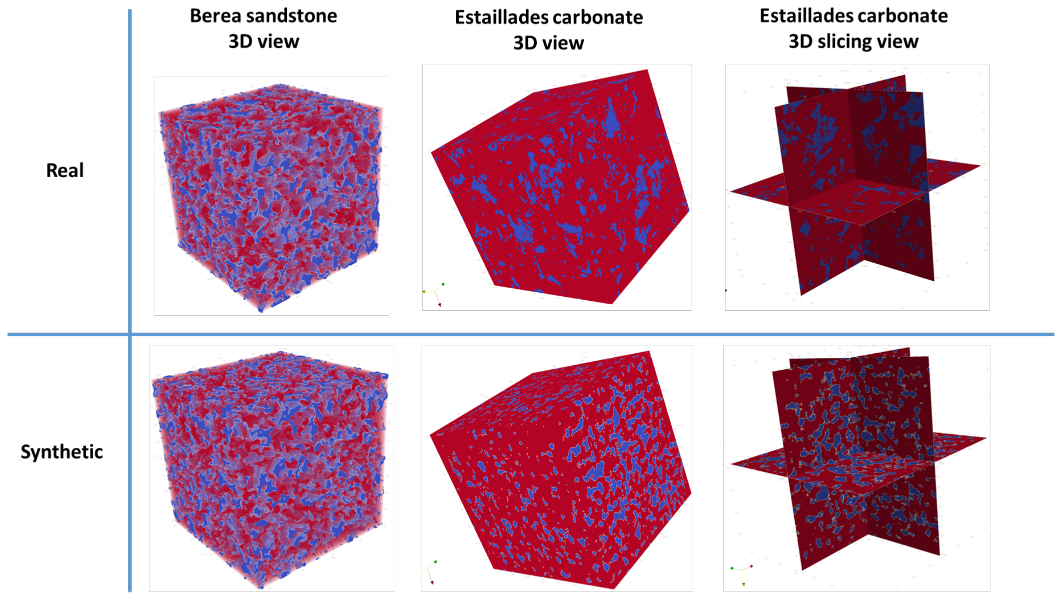

Figure 5. The selected synthetic 3D image and the real images comparison in 3D view and 3D slicing view

4. Conclusion

In this study, the GAN models are created based on the improved the sub-sampling approach to reconstruct the 3D realizations of relative homogeneous Berea sandstone and relative heterogeneous Estaillades carbonate, they show promising capabilities to represent rock samples' physical properties in 3-dimensional space. The network shows good capabilities of reconstructing homogeneous rock sample and still need to be improved for obtaining good representations of heterogeneous porous media. Data augmentation pre-processing speeds up the convergence of the training process and also shows advantages of capturing some level of heterogeneities in 3D images. Future work will include applying GANs for multi-properties characterizations in porous media, and improvement of the network configurations and training stabilities in order to enhance the generalization capability to deal with more complex porous media problems.

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