Reconstructing Pore Images Using Generative Adversarial Networks

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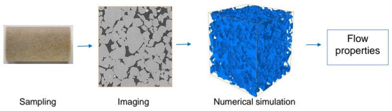
Introduction

Motivation

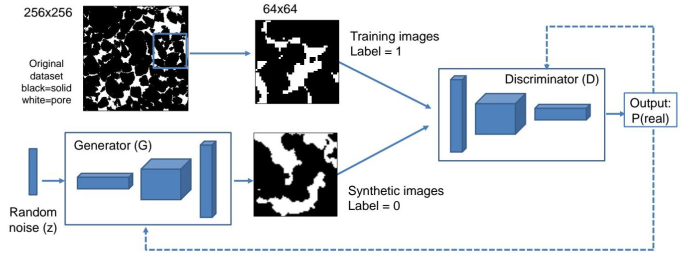
- Flow properties (porosity and permeability) of porous media can vary due to rock heterogeneity
- Recreating variations of the pore network can be time-consuming (both in the lab and computationally)
- Recent advances in deep learning show promising use of GANs for rapid generation of 3D images with no a priori model [1,2]
    - Models used: vanilla DCGAN, conditional GAN
    - Ways to improve training/image quality?



Objective

- Investigate effects of changing network parameters, e.g. loss function, on a 2D and 3D DCGAN [2]
- Evaluate model performance against real images using morphological properties

Model Architecture and Training



DCGAN $\min_G \max_D \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z))]$

DCGAN-GP $\min_G \max_D \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z))] + \lambda \mathbb{E}_x[(||\nabla_x D(x)||_2 - 1)^2]$

DCGAN-WGP $\min_G \max_D \mathbb{E}_{x\sim p_{\text{data}}(x)}[D(x)] - \mathbb{E}_{z\sim p_z(z)}[D(G(z))] + \lambda \mathbb{E}_x[(||\nabla_x D(x)||_2 - 1)^2]$

2D DCGAN model:

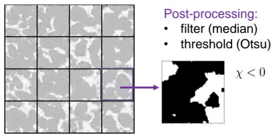
Layer	Type	Filters	Kernel	Stride	Padding	Batch Norm	Activation
Generator							
1	ConvTransp2D	512	4 x 4	1	0	Yes	ReLU
2	ConvTransp2D	256	4 x 4	2	1	Yes	ReLU
3	ConvTransp2D	128	4 x 4	2	1	Yes	ReLU
4	ConvTransp2D	64	4 x 4	2	1	No	Tanh
Discriminator							
1	Conv2D	64	4 x 4	2	1	No	LeakyReLU
2	Conv2D	128	4 x 4	2	1	Yes	LeakyReLU
3	Conv2D	256	4 x 4	2	1	Yes	LeakyReLU
4	Conv2D	512	4 x 4	1	0	No	Sigmoid

Strategies:

- Modified generator loss function – $\log D(G(z))$
    - Prevent vanishing gradients
- One-sided label smoothing
- Vanilla DCGAN with gradient penalty
- Wasserstein distance with gradient penalty – shown to improve convergence, no batch norm layer [4]

Data Acquisition & Evaluation

Image size (voxels)	256 x 256 x 256	
Voxel size	6.12 um	
Subvolume spacing	16 pixels	
Training image size	64 x 64	64 x 64 x 64
# of training images	36,864	12,195



4x4 grid of G(z) output images after training

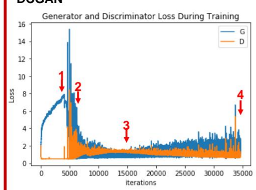
Evaluation metrics (2D Minkowski functionals)

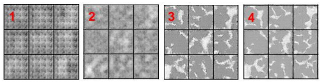
- Area ~ available pore (white) space
- Perimeter ~ pore shape
- Euler characteristic, χ ~ connectivity

$$\chi = n_{connected} - n_{holes}$$

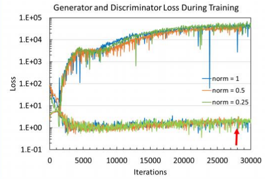
Results

DCGAN





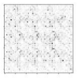
Model	Pore area	Perimeter, $\times 10^{-2}$	Euler characteristic, $\chi \times 10^{-4}$
Train set	18.4 ± 7.8	6.94	-3.89
DCGAN	21.6 ± 7.7	6.82	-4.28
DCGAN-GP	20.2 ± 8.1	6.87	-4.01

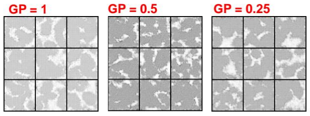


Gradient penalty norm	Pore area, %
1	20.2 ± 8.1
0.5	21.7 ± 7.5
0.25	20.3 ± 7.8

3D DCGAN

Longer training?





Conclusion

- DCGAN model performs well for 2D case using the log loss function with and without the gradient penalty term
- Adjusting the Lipschitz constant can limit the discriminator's learning capacity, but had no significant effect on our dataset (may be too simple)
- Adjusting discriminator parameters in the 3D model helps to speed up training and prevent overfitting

Future work

- Train on larger areas/volumes to reduce variability in porosity, etc.
- Improve training of 3D GAN to create reconstructions of the pore network as inputs into numerical solvers for fluid flow

References and Acknowledgements

[1] L . Mosser, O. Dubrule, and M. J. Blunt, "Reconstruction of three-dimensional porous media using generative adversarial neural networks," Physical Review E, vol. 96, no. 4, 2017.
[2] J. Feng, Q. Teng, X. He, and X. Wu, "Accelerating multi-point statistics reconstruction method for porous media via deep learning," Acta Materialia, vol 159, 2018.
[3] A. Radford, L. Metz, and S. Chintala, "Unsupervised Representation Learning With Deep Convolutional Generative Adversarial Networks," arXiv:1511.06434, 2016.
[4] I. Gulrajani, F. Ahmed, M. Arjovsky, V. Dumoulin, and A. Courville, "Improved Training of Wasserstein GANs," arXiv:1704.00028, 2017.

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