3D Reconstruction of Porous Media using Generative Adversarial Networks

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Overview

• Motivation
• Generative Adversarial Networks (GAN)
• Reconstruction Metrics
• Application to CT Images of Porous Media
• Discussion
• Conclusions - Outlook
Motivation – Digital Rock and Core Analysis

• Physical Representation:
  • Core
  • Core Plugs
  • (Micro) CT Scans
  » Multi-Phase Flow
  • FIB-SEM

Physical Experiments:
• RCAL – SCAL

Numerical Experiments
• Pore-Network Models
• Direct Simulation

Digital Representation:
• Create 3D synthetic realizations based on Micro-CT Images as input to numerical experiments
• Perform ensemble numerical experiments
Reconstruction Methods

Stochastic Methods

MPS

Training Image

Realization

Pattern Matching

3D - Orthoslices: Okabe 2005

Boolean Models

Neural Networks

Other Methods: Simulated Annealing, SIS, PGS, Image Quilting
Generative Adversarial Networks

- Consist of two differentiable functions:
  - Generator (G) and Discriminator (D)
    » Convolutional neural networks

- Discriminator’s goal:
  » Distinguish real and generated samples

- Generator’s goal:
  » Samples from latent space
    - Generates stochastic reconstructions
  » “Fool” discriminator with generated samples

- Discriminator tries to approximate:
  \[
  \frac{p_{data}(x)}{p_{data}(x) + p_{generated}(x)}
  \]

- Continuously update weights of G and D
- Convergence:
  \[
  p_{data}(x) = p_{generated}(x)
  \]  
  (Goodfellow et. al. 2015)
Generative Adversarial Neural Networks

Image Dataset (500³ voxels) → Training Images (64³ voxels) → Image Pre-Processing

Latent Random Vector z

Maximize D(G(z))

Training Image X
Label: 1

Synthetic Image Y
Label: 0

Synthetic Realizations

Generator

Discriminator
Optimizes the assignment of labels to X and Y
Reconstruction Metrics

- **Statistical Properties**
  - Two-Point Probability Function $S_2(r)$
    - Radial Average / Directional
    \[ S_2(r) = \mathbb{P}(x \in P, x + r \in P) \text{ for } x, r \in \mathbb{R}^d \]
  - Chord length $l_C$

- **Minkowski Functionals**
  - Porosity $\phi$
  - Specific Surface Area $S_v$
  - Specific Euler Characteristic $\chi_v$

- **Single Phase Permeability**
  - Stokes Equations
Spherical Beadpack

- Spherical Particles
- Equal Diameters
- Random Packing
- Segmented Training Image
- Image Size:
  - $500^3$ voxels
- Training Images:
  - Extract Subdomains ($128^3$):

Original Image  \[\rightarrow\]  Training Images

3D Micro-CT Render
500 voxels
Beadpack Dataset

Training Image

Training: 20 hours
Generation: 5 seconds
Training Images: $128^3$ voxels

Synthetic Image
Beadpack – $S_2(r)$ and Morphological Analysis

- Captures “Hole-Effect”
- Spherical shapes complex to learn from data only
Berea Sandstone Dataset

Training Image

Synthetic Image

Training: 15 hours
Generation: 2 seconds
Training Images: 64^3

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Berea – $S_2(r)$ and Morphological Analysis

$\phi_{GAN} = 0.20 \pm 0.007$

$\phi = 0.20$

Porosity $[-]$

Specific Surface Area $\frac{1}{{\text{voxel}}}$

Specific Euler Characteristic $\frac{1}{{\text{voxel}^3}}$

Permeability $[m^2]$
Berea - Permeability Evaluation

- Computed permeability vs. effective porosity
  
- Domain size ($128^3$ voxels):
  - 2x TI size ($64^3$ voxels)

- Synthetic reconstructions show $k \sim \phi_{eff}$ with:
  - Similar trend
  - Magnitude

- Allows effective property to be estimated for ensemble of stochastic reconstructions
Ketton Dataset

Training Image

Fragments and Micro-porosity?

Synthetic Image

Training: 15 hours
Generation: 2 seconds
Discussion

• Method is independent of imaging technique

• Training time is long (10s hours) – reconstruction time fast (seconds)

• Very active research topic in ML community
  • Improved GAN formulations – more stable and quality estimates

• No direct control over reconstruction metric
  • Requires continuous monitoring of derived properties

• Computational Scaling:
  • Linear in number of voxels
  • Very fast on CPU and GPU
  • Main requirement: Memory
Conclusions and Outlook

• Presented a new method for stochastic image reconstruction based on generative adversarial neural networks (GAN)

• GANs allow computational efficient sampling of large 3D reconstructions
  • Capture two-point statistics, image morphology and permeability

• Outlook: GANs as a tool to bridge scales?
Thank you!
Questions?
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Pre-print: arXiv:1704.03225
Code: github.com/LukasMosser/PorousMediaGAN