Fast and Scalable Digital Rock Construction using Spatially Assembled Generative Adversarial Neural Networks

Sung Eun Kim[1], Jonghyun Harry Lee[1], and Hongkyu Yoon[2]

[1]Civil and Environmental Engineering, University of Hawaii at Manoa, Honolulu, HI, USA; [2]Geomechanics Department, Sandia National Laboratories, Albuquerque, NM, USA

Background

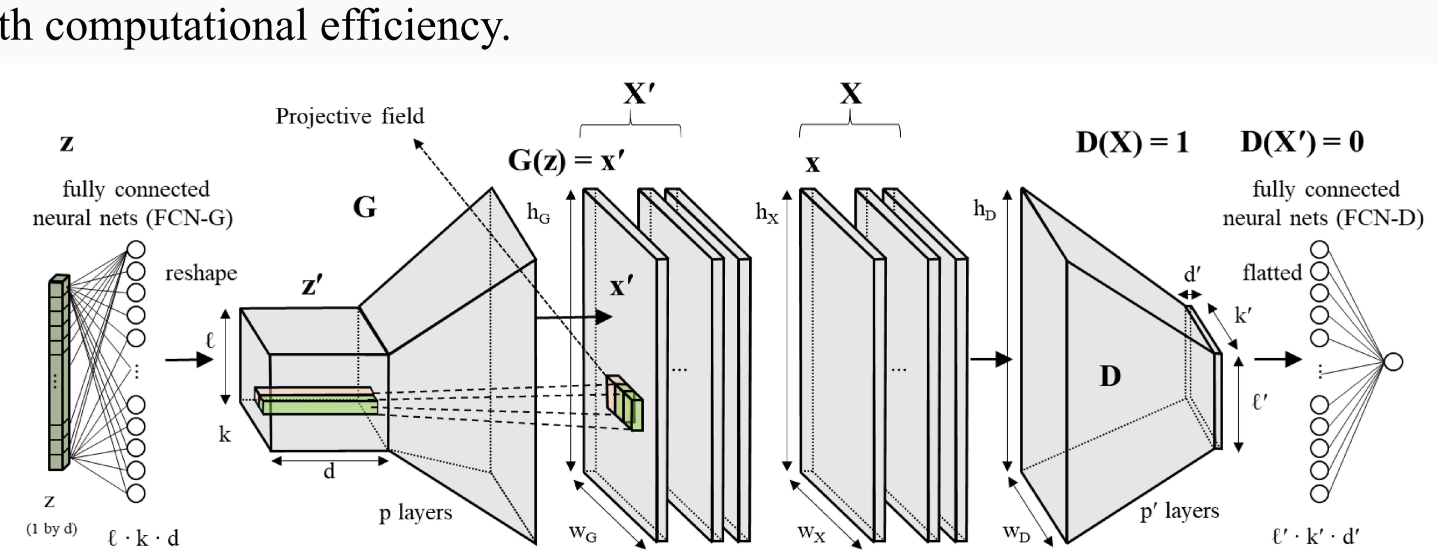
- **Rock reconstruction**
  - The rock with complex morphological geometry and compositions such as shale and carbonate rocks, is **typically characterized with sparse field samples** because of an **expensive and time-consuming characterization process**.
  - **Accurate capture and realization** of the underlying complex stochastic properties of the geological texture **with a limited set of samples** has long been an important issue in the rock reconstruction.
- **Geostatistical methods**
  - Many geostatistical methods such as multiple-point statistics have been developed and achieved in many successful applications.
  - But they suffer from **limitations inherent to the algorithms** : **computational cost, visual artifacts, and a low variability in the realization**
- **Generative models using deep learning**
  - Recently, Generative Adversarial Neural Networks (GANs) have demonstrated remarkable results in terms of image or texture synthesis.
  - Variation of GANs-based models have been developed and applied to the rock reconstruction.
  - However, the rock reconstruction with GANs framework still requires **considerable computational costs** which can be prohibitive for high-resolution applications (2D and 3D) and **scalable applications** due to a constraint on the size of training samples.

Objective

- To improve the computational cost and scalability of standard GANs framework, we proposed a **fast and scalable** GANs framework, called **the spatially assembled GANs framework (SAGANs).**

Generative Adversarial Neural Nets (GANs)

- GANs are deep learning frameworks to develop generative models via adversarial two neural network models (G and D model).
- G model (generator) – a generative model generates samples through learning to map from a latent space to a particular data distribution of real samples
- D model (discriminator) – a discriminative model determines whether given samples were a generated (fake) sample by G model or real samples.
- Deep Convolutional GANs (DCGANs) : GANs adopting deep convolutional nets.
- Fully convolutional nature of DCGANs allows the stable training and the generation of many samples that contain the similar properties to training data and with computational efficiency.

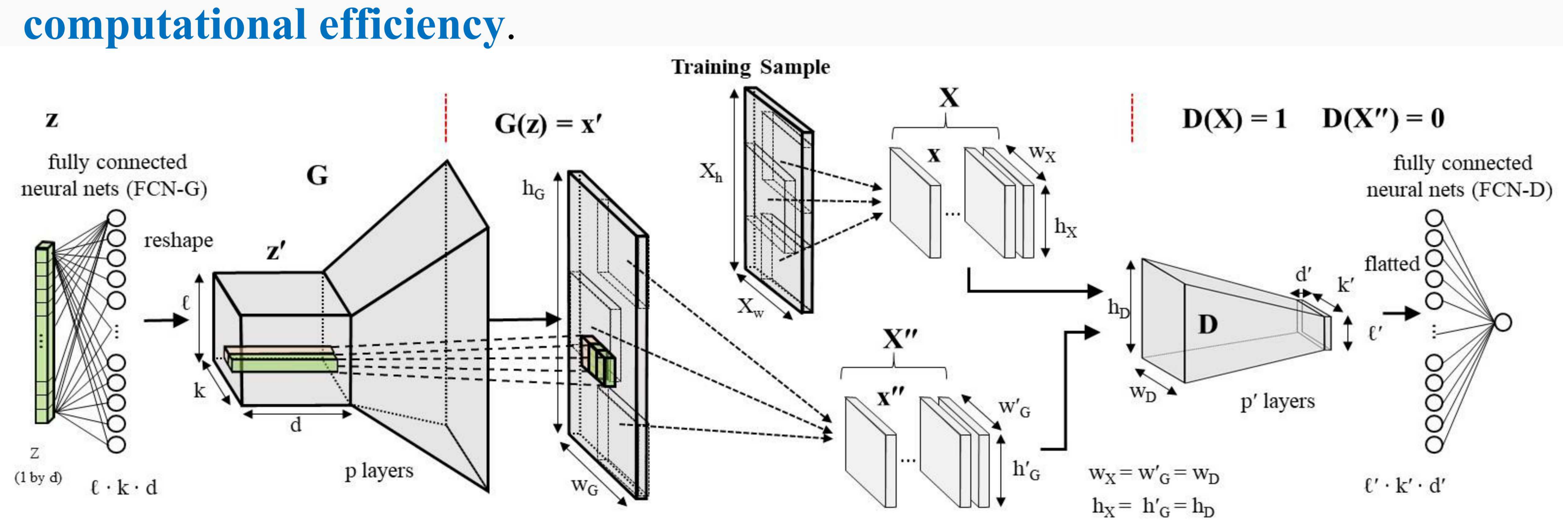


Loss of D model: $\min J^{(D)} = -\frac{1}{2}\Big\{\mathrm{E}_{x\sim P_{data}(x)}[logD(x)] + \mathrm{E}_{z\sim P_z(z)}[log(1-D(G(z)))]\Big\}$

Loss of G model: $\min J^{(G)} = -\frac{1}{2}\mathrm{E}_{z\sim P_z(z)}[log(D(G(z)))]$

Spatially Assembled GANs (SAGANs)

- **Main conceptual idea**
  The local probability in the disassembled generated images (segments) is estimated by the discriminator, and then assembled into a global probability.
- **No architectural constraint between G and D model**
  The size of the generated output in the G model need not to be identical to the size of the input of D model.
- This enable SAGANs to produce the realizations with the **scalability and computational efficiency**.

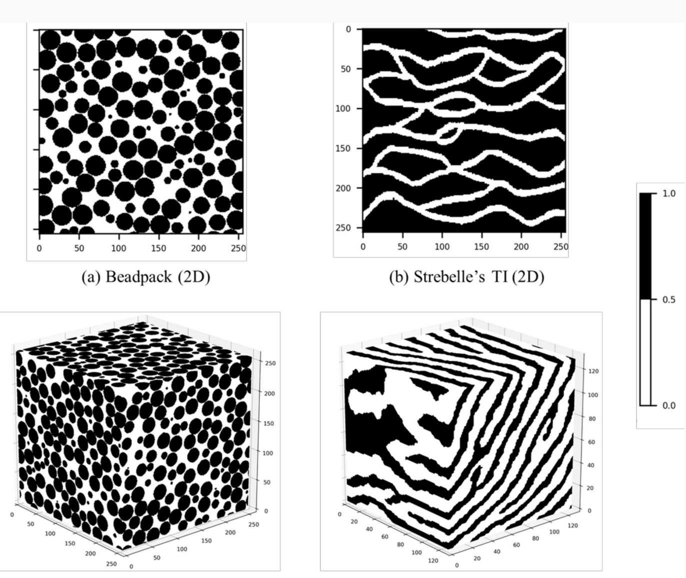


Loss of D model: $\min J^{(D)} = -\frac{1}{2}\{\mathrm{E}_{x\sim P_{data}(x)}[logD(x)] + \frac{1}{n}\sum_{i=1}^{n}\mathrm{E}_{z\sim P_z(z)}[log(1-D(x_i^{''}))]\}$

Loss of G model: $\min J^{(G)} = -\frac{1}{2n}\sum_{i=1}^{n}\mathrm{E}_{z\sim P_z(z)}[log(D(x_i^{''}))]$

Development of DCGANs & SAGANs

•Training Images



< Training images (TIs) used in this study >

- Three training images (TIs) datasets widely used for geostatistical simulation.
- These datasets have **simple structures, but** are proven to be **very challenging** as the training image for the GANs
  - the long-range connectivity
  - discrete and dispersing nature

< Summary of training images (TIs) >

	Original datasets		This study		Experiment case
	size	color scale	size	color scale	
Strebelle's TI	250*250*1	Binary, 0/1	256*256	Binary, 1/0	2D
Beadpack	500*500*500*1	Gray, 0 - 255	256*256*256		2D
			256*256*256*1		3D
Fold Aquifer	180*150*120	Binary, 0/1	128*128*128*1		3D

• Architecture and Parameters of GANs

- The architecture of deep convolution neural networks for DCGANs and SAGANs was constructed based on the guidelines proposed by Radford et al. (2016)
- All computational works in this study were performed using the same computer equipped with two NVIDIA TITAN-V GPU cards.

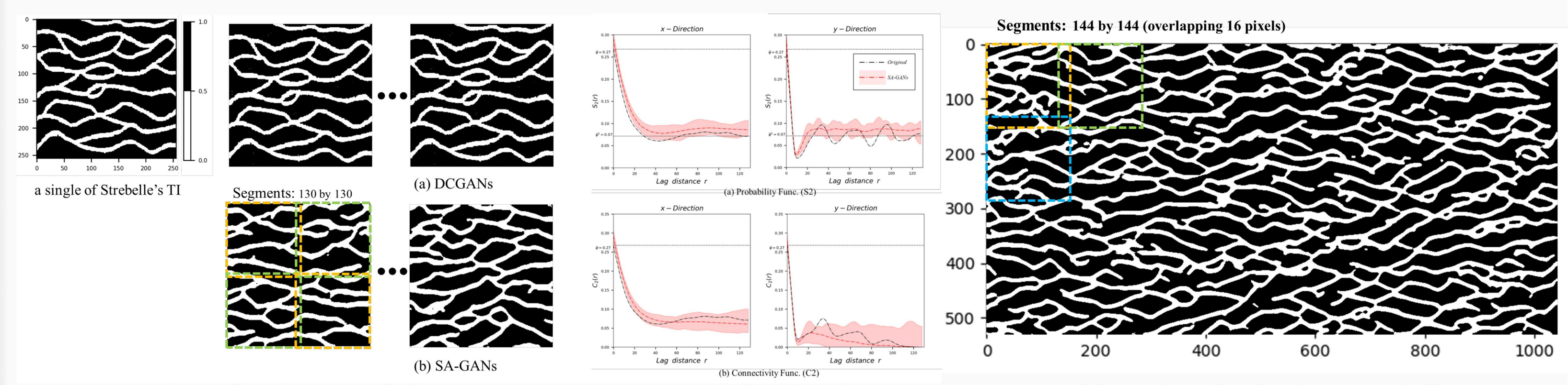
< Architecture and Parameters applied to GANs in this study >

Parameter	Value
Latent Space Dimension, z	100
Convolutional Layers / Filters	3 to 5 layers, filters (4/8/16/32/64/128) Symmetric for D and G model
Kernel Size	$3 \times 3 \times 3$ (for 3D TIs), 5×5 (for 2D TIs)
Optimizer	Adam with mini-batch
Learning Rate / Momentum	$2 \times 10^{-4}/0.5$
Epoch / Mini-batch Size	Max 100,000 / 4 to 64
Dropout rate / Batch normalization Momentum	0.25 / 0.8
Activation Function	ReLu, tanh (G model) / LeakyReLu with alpha = 0.2, sigmoid (D model)
Loss Function	Binary Cross-entropy

Experimental Results

• Strebelle's TI (2D)

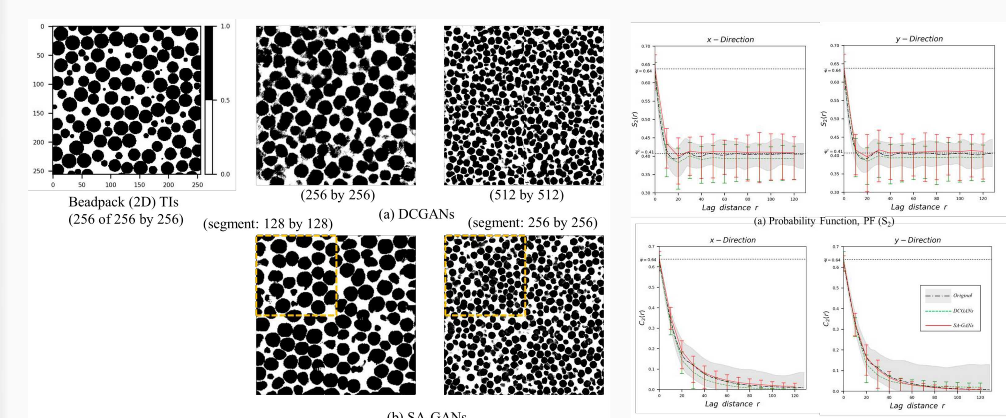
- Standard GANs (DCGANs) with a single TI generated the same realization of images as the TI.
- **SAGANs produced the various patterns and arbitrary size of realization with keeping its statistics (the long-range connectivity) even in a single TI.**



<Comparison of results on Strebelle's TI> <Morphological descriptor> <Arbitrary size of realization on Strebelle's TI > (1,040 by 528)

• Beadpack (2D)

- Both DCGANs and SAGANs produced the realizations with various size of spherical beads.
- Beads in the realizations by SAGANs have more spherical shape and less overlapped each other (well-spread) than the realizations by DCGANs.

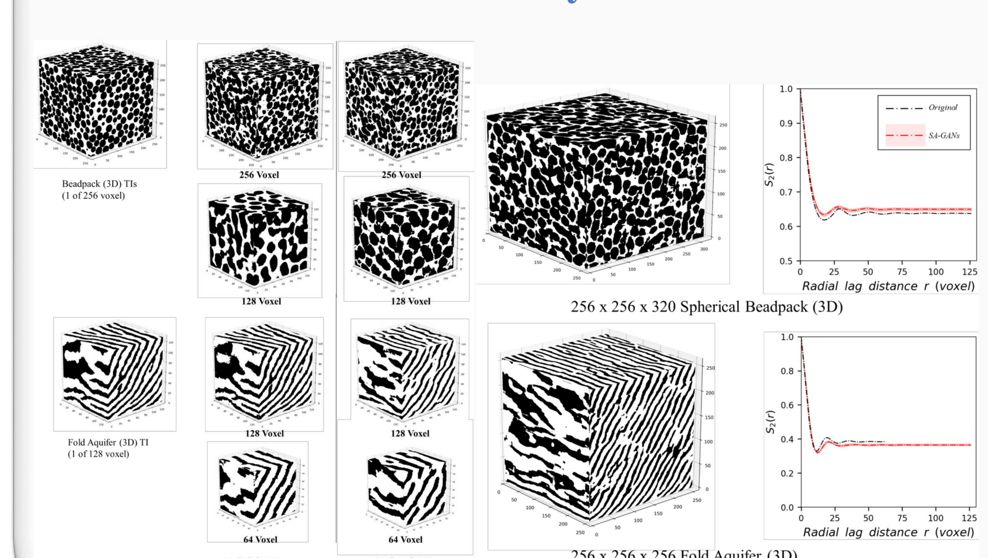


<Comparison of results on Beadpack(2D) > <Morphological descriptor>

- DCGANs have the limits in generating the arbitrary large size of realizations due to the cropping area (or the seam) of the original TIs.
- **SAGANs can produce seamless arbitrary size of realization.**

• Beadpack (3D) & Fold Aquifer

- **SAGANs could produce the 3D realizations of the arbitrary larger size and with diversity even in a single of 3D TI.**
- **SAGANs could also produce the larger size of 3D realizations with low computational time and load which DCGANs could not generate due to the lack of GPU memory.**



<Comparison of results on 3D TIs > < Arbitrary size of 3D realization by SAGANs >

< Comparison of training time between SA-GANs and DCGANs >

TIs	Generated Size	Model	Segment size	Training Time (Sec.) (Decrease)
Beadpack (2D) (256 of 256 × 256)	256 × 256	DCGANs		45.54
		SA-GANs	128 × 128	27.70 (-39%)
	512 × 512 (Larger than TIs)	DCGANs		120.92
		SA-GANs	128 × 128	51.26 (-58%)
Strebelle TI (2D) (1 of 256 × 256)	256 × 256	DCGANs		53.70
		SA-GANs	130 × 130	22.92 (-57%)
	512 × 512 (Larger than TIs)	DCGANs		196.94
		SA-GANs	131 × 131	61.17 (-69%)
	528 × 1040 (Larger than TIs)	SA-GANs	144 × 144	120.86
Beadpack (3D) (1 of 256 × 256 × 256)	128 × 128 × 128	DCGANs		909.83
		SA-GANs	64 × 64 × 64	250.78 (-72%)
	256 × 256 × 256	DCGANs		6531.66
		SA-GANs	64 × 64 × 64	839.30 (-87%)
	256 × 256 × 320 (Larger than TIs)	SA-GANs	64 × 64 × 64	1013.89
Fold Aquifer (3D) (1 of 128 × 128 × 128)	64 × 64 × 64	DCGANs		231.00
		SA-GANs	34 × 34 × 34	81.30 (-65%)
	128 × 128 × 128	DCGANs		1066.1
		SA-GANs	66 × 66 × 66	234.06 (-78%)
	256 × 256 × 256 (Larger than TIs)	SA-GANs	67 × 67 × 67	839.26

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