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

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Background

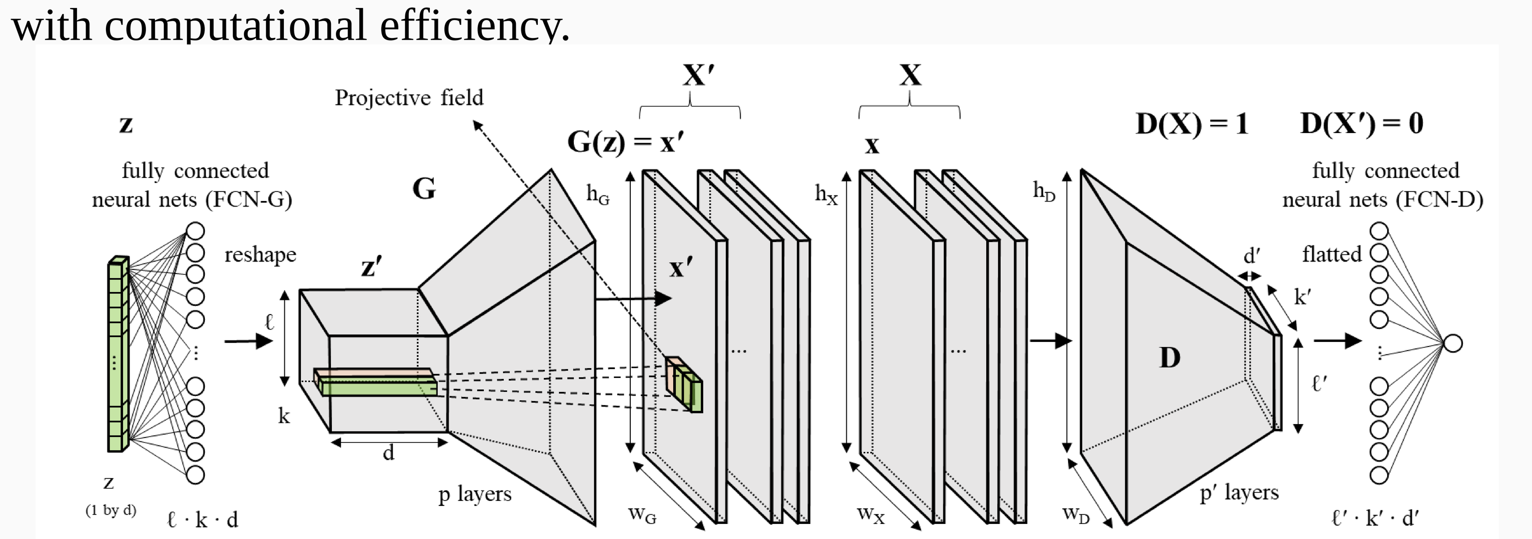
- **Rock reconstruction**
  - The rock with complex morphological geometry and compositions such as shale and carbonate rocks, is **typically characterized with sparse field samples** because of an **expensive and time-consuming characterization process**.
  - **Accurate capture and realization** of 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 Networks (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 networks.
- 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.

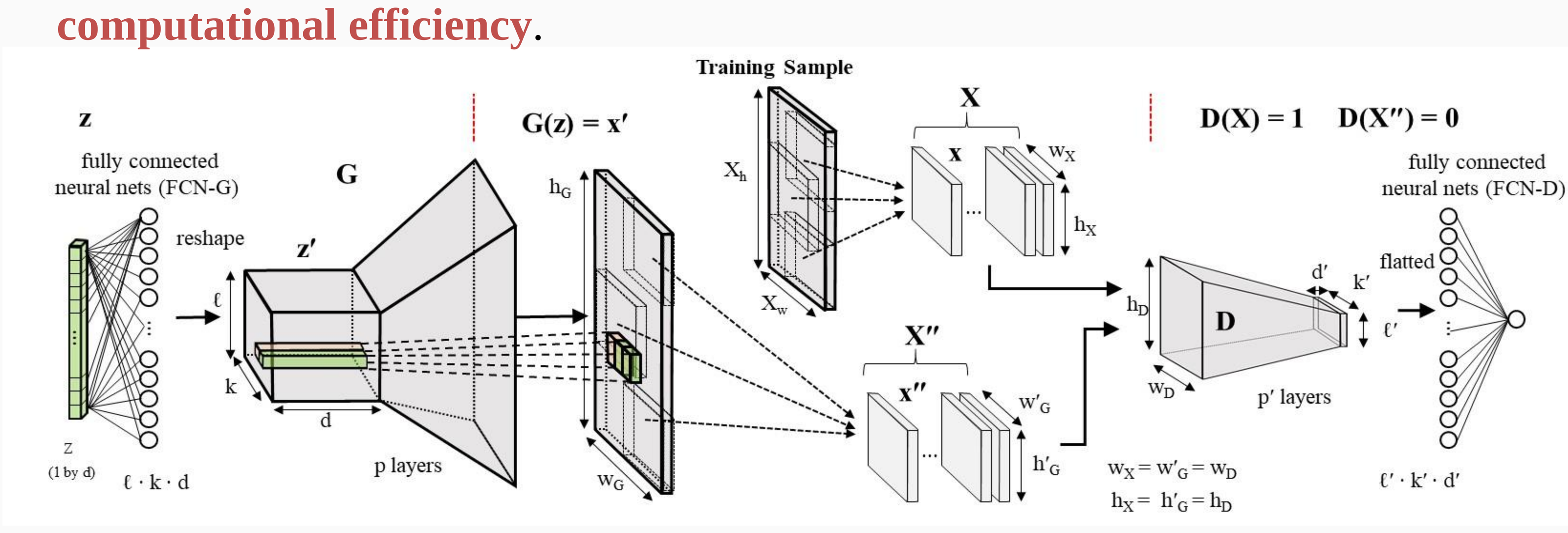


Loss of D model: $$\min J^{(D)} = -\frac{1}{2}\left\{\mathrm{E}_{x\sim P_{data}(x)}[logD(x)] + \mathrm{E}_{z\sim P_z(z)}[log(1-D(G(z)))]\right\}$$

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**.

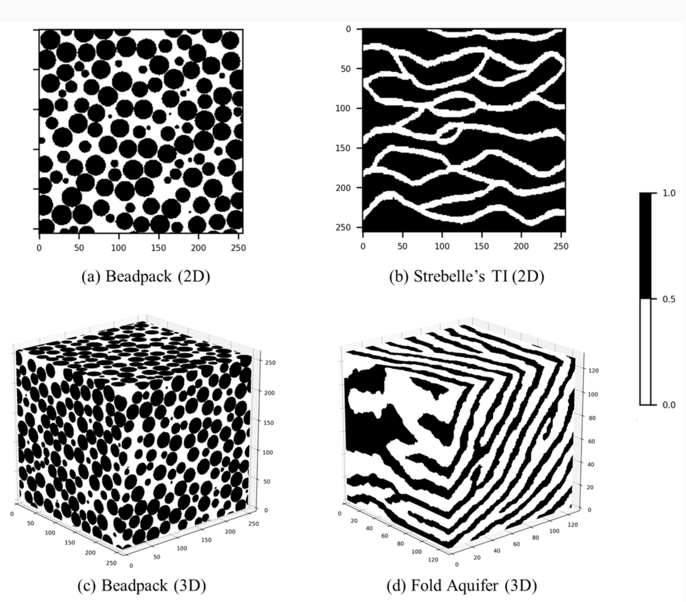


Loss of D model: $$\min J^{(D)} = -\frac{1}{2}\{\mathrm{E}_{x\sim P_{data}(x)}[logD(x)] + \frac{1}{n}\sum_{i=1}^{n}\mathrm{E}_{z\sim P_z(z)}[log(1-D(x_i''))]\}$$

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. (2015)
- All computational works in this study were performed using the same computer equipped with two NVIDIA TITAN-V GPU cards.

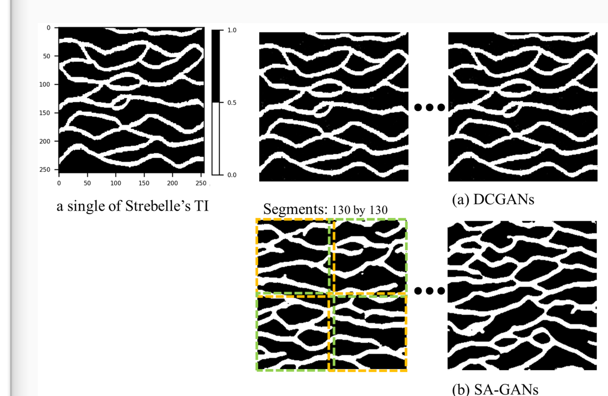
< Architecture and Parameters applied to GANs in this study >

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	$3\times3\times3$ (for 3D TIs), 5×5 (for 2D TIs)
Optimizer	Adam with mini-batch
Learning Rate / Momentum	$2\times10^{-4}/0.5$
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

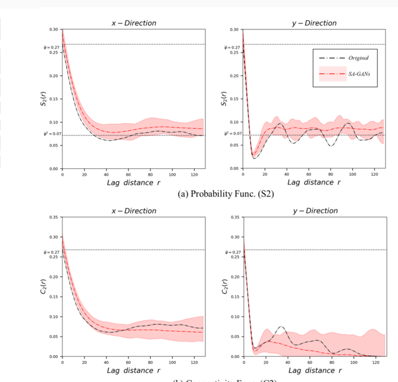
Experimental Results

• Strebelle's TI (2D)

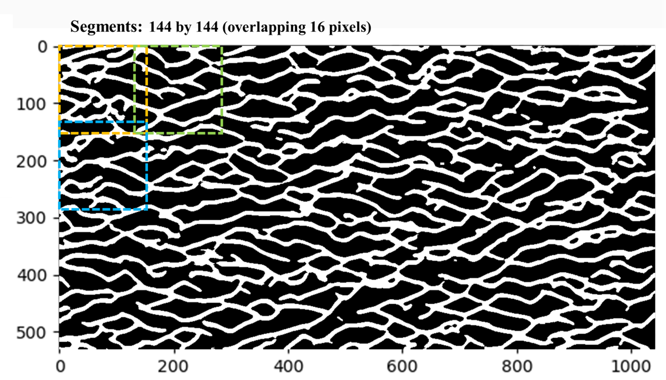
- Standard GANs (DCGANs) with a single TI generated the same realization of images as the TI.
- **SAGANs produced the various patterns and arbitrary size of realization with keeping its statistics (the long-range connectivity) even in a single TI.**



<Comparison of results on Strebelle's TI>



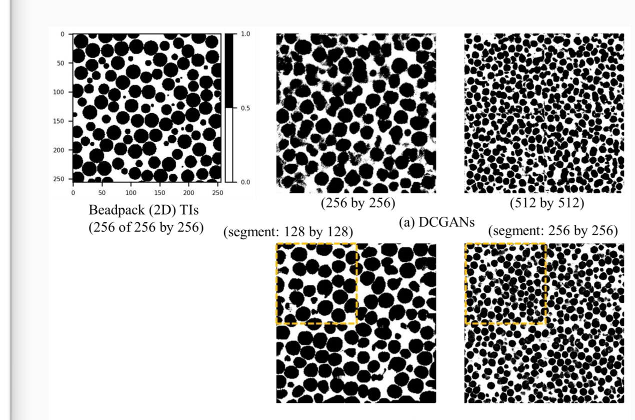
<Morphological descriptor>



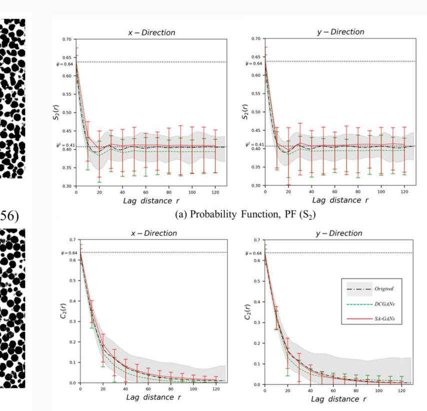
<Arbitrary size of realization on Strebelle's TI > (1,040 by 528)

• 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) >

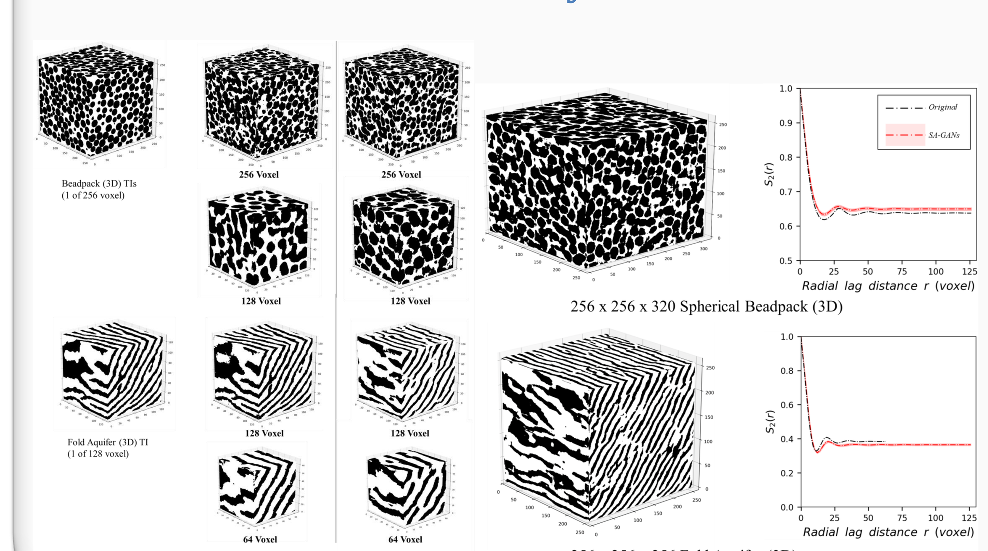


<Morphological descriptor>

- 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

References

Radford, A., Metz, L. & Chintala, S. (2015) Unsupervised representation learning with deep convolutional generative adversarial networks. CoRRabs/ 1511.06434

Acknowledgement

This study was partly supported by **the National Science Foundation EPSCoR Program Award OIA #1557349** and the Faculty Research Participation Program at the **U.S. Engineer Research and Development Center**, Coastal and Hydraulics Laboratory administered by the **Oak Ridge Institute for Science and Education** through an interagency agreement between the U.S. Department of Energy and ERDC. This work was also supported by the Laboratory Directed Research and Development program at **Sandia National Laboratories**. This poster describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the United States Government.