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Adapting the StyleGAN Architecture for arbitrary shape 2D and 3D Facies Generation

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Abstract Summary.

This work presents a novel adaptation of the StyleGAN architecture to generate high-resolution 2D and 3D geological volumes for geophysical applications. Traditional StyleGAN models are constrained by fixed-resolution outputs, limiting their utility in geological modeling. To address this, we introduce architectural modifications that enable flexible input and output resolutions, allowing for the generation of arbitrarily sized geophysical grids. Key innovations include restructuring latent vectors into spatially aware latent volumes, adapting the discriminator to output localized judgments, and replacing fully connected layers with convolutional layers. Additionally, we implement geospatial conditioning using well and seismic data, enabling the generation of geologically consistent models. Our results demonstrate the model's ability to synthesize complex geological facies across varying resolutions and volumes without retraining, offering a scalable solution for subsurface modeling in petroleum exploration.

Introduction

The generation of realistic synthetic images has become a promising tool in petroleum applications, particularly in the fields of geophysics and geological modeling. In this work, we propose a modification to the original StyleGAN architecture – traditionally limited to fixed-sized images — to enable the generation of geophysical volumes at arbitrarily big grids and in both 2D and 3D dimensions. The main limitation of StyleGAN 1, the architecture that we adopted to our current project phase, lies in its requirement that the size of the generated images matches the size of the training images (Karras et al., 2019). To overcome this constraint, we restructured the network to accept latent input tensors (z) with additional spatial dimensions and training images with arbitrary shapes, while preserving spatial coherence and visual quality.

Method and/or Theory

Our geological volume is represented as a 4D tensor, where the first dimension corresponds to the number of channels representing geological facies (proportion of each facies in each pixel), followed by the spatial dimensions x, y, and z. The images for training are composed of patches that are extracted from the 4D big volume from the training dataset using strides to keep the connection between the patterns.

In our approach the latent vectors become latent volumes, also represented as 4D tensors, where the first dimension is the number of channels which corresponds to the vector number of features in the original NVidia implementation (128 in StyleGAN architecture). In this context, our approach uses the concept of image resolution as the smallest spatial size of the images generated by the Generator network, i.e. the image size when the latent volume has 1 voxel. We modified the Discriminator architecture to process the entire generated geological volume, and output a volume of logits, instead of a single logit. Conceptually is equivalent to a localization of the Discriminator judgment of the input image: instead of a single judgment regarding the input image, the Discriminator outputs a judgment of the regions inside the input image. The losses of the GAN are adapted to compute the mean of the logit volumes output by the Discriminator to update the weights of the networks.

Regarding the Generator architecture, we substituted all the fully connected layers with Convolution layers with 1x1 kernels.

The original StyleGAN implementation has capability for semantic conditioning, i.e. generating an image/volume given a vector of features. We have adapted the StyleGAN architecture to allow for conditioning with geospatial information, such as wells, horizons or seismic derived facies trends. The input geospatial conditioning is upscaled to a grid and fed to Generator as a 4D tensor (features channels plus the 3D spatial dimensions). Each Synthesis Block in the Generator works on a certain resolution level (2/8, up to 1), so the conditioning information is downscaled to the required resolution and processed by each Synthesis Block together with the activation tensors from the previous Synthesis Block.

Given geospatial conditioning data, we have implemented utility functions to compute the input latent spatial size necessary to comply with the conditioning data spatial size based on the number of synthesis blocks.

These changes contributed to a more scalable and flexible GAN framework for geological data synthesis.

Results

We successfully trained the modified StyleGAN using various combinations of image resolution such as (6, 16, 16, 16), (6, 32, 32, 32) and (6, 64, 64, 64), along with patch sizes like 32, 40, 64 and 80), among others. The model was able to perform inference on larger volumes such as (6, 255, 69, 189), (6, 128, 128, 128), and (6, 200, 64, 200) without retraining. This flexibility allows the generation of complex geological facies models over large areas, even when computational resources are limited during training.

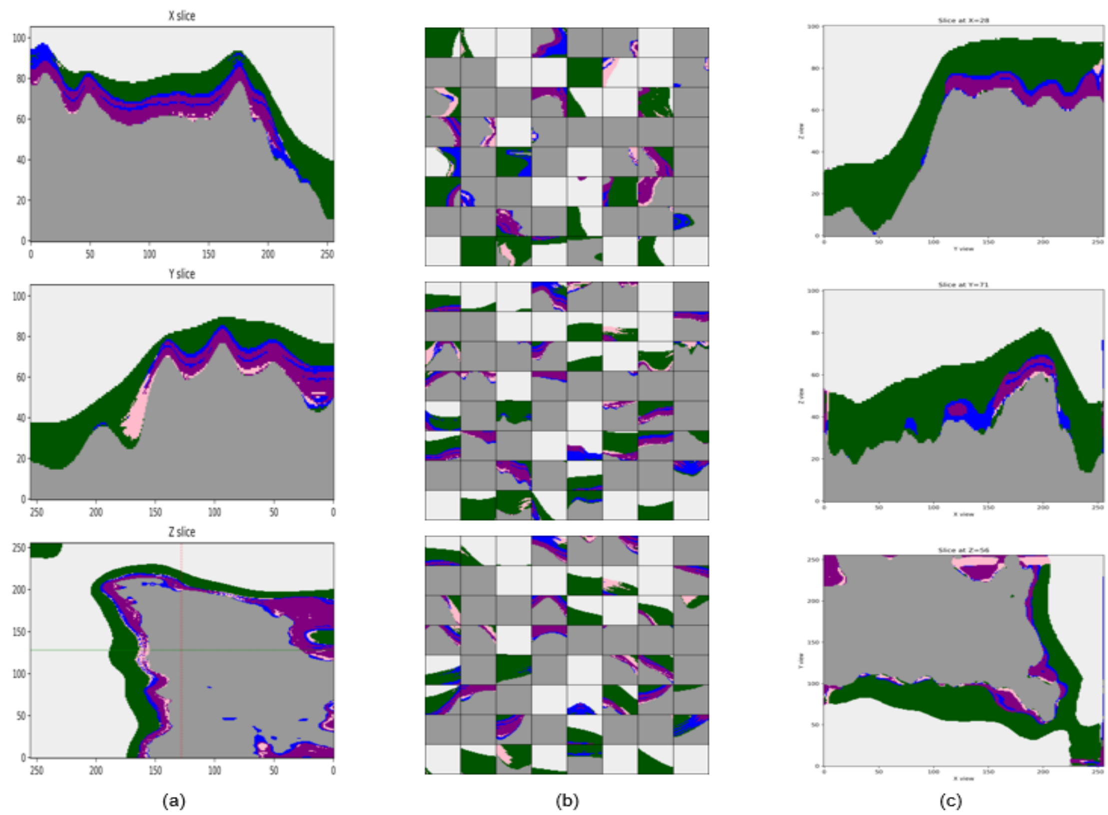

Figure 1: Inference results showing orthogonal slices of a generated 3D geological volume. From top to bottom and across X, Y, and Z views: (a) representative slices from the training dataset,

(b) a grid of 64 patches extracted from training volumes of size 32×32×32, and (c) an inference result from the trained model on a full volume of size 256×256×128.

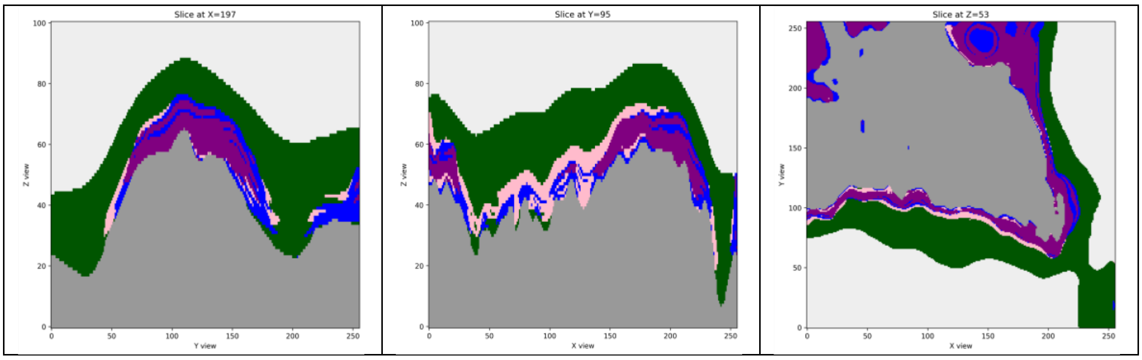

Figure 2: Inference results showing orthogonal slices of a generated 3D geological volume. From left to the right across X, Y, and Z views we have an inference result from the trained image resolution of 64x64x64 and patch size of 80x80x80 model on a full volume of size 256×256×128.

Conclusions

Our results demonstrate that the adapted StyleGAN architecture maintains structural fidelity and enables scalable, high-resolution generation of 3D geological models. This contribution opens new possibilities for applying machine learning to geosciences, particularly in scenarios that demand high-resolution, volumetric modeling of real-world subsurface structures.

References

Karras, T., S. Laine, and T. Aila, 2019, A style-based generator architecture for generative adversarial networks: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 4401–4410.

Song, S., T. Mukerji, and J. Hou, 2021, Geological facies modeling based on progressive growing of generative adversarial networks (GANs): Computational Geosciences, 25, 1251–1273.