Simulation Domain Generation for Characterization of Shale Source Rocks

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Overview

- Shale gas has accounted for a majority of the increase in domestic energy production, contributed substantially to reduction in CO_2 emissions since 2009 [10, 4]
- Rock features on length scales from $\mathcal{O}(10^{-9}\text{ m})$ to $\mathcal{O}(10^{+2}\text{ m})$ affect recovery in shales
- Nanoscale imaging in conjunction with digital rock physics critical for study of shales [6, 8, 3]
- Central challenges: nanoimaging expensive, time-consuming and/or sample destructive; acquired in 2D when 3D needed for characterization; data scarcity
- Multimodal imaging emerging area for shale characterization [1], opportunity for high-resolution and sample-preserving imaging using deep learning-based characterization workflow (Fig. 1) [2]

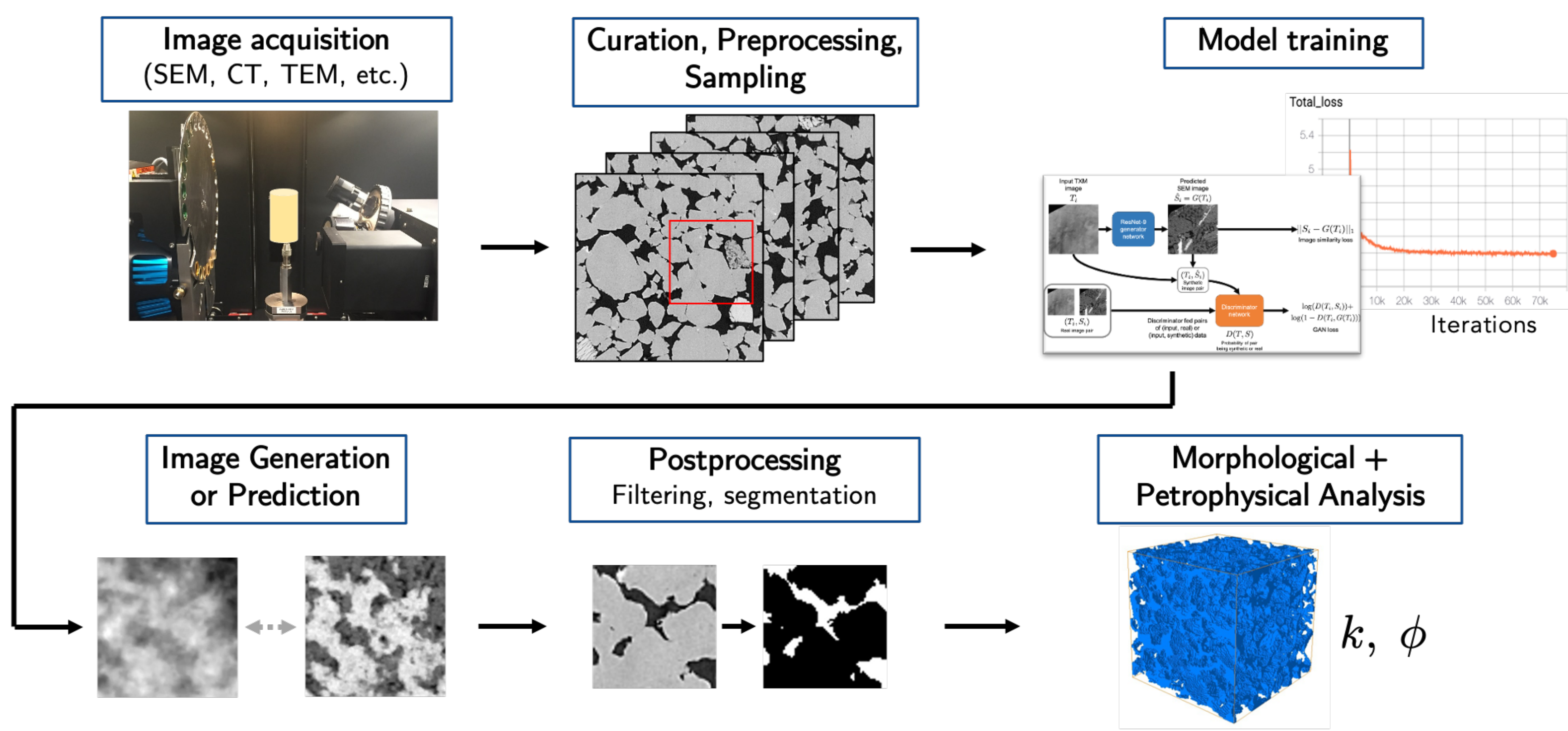

Figure 1: Image-based characterization workflow

Multimodal Image Dataset

- Vaca Muerta shale sample (600 μm diameter core) is initially imaged with micro-computed tomography, then a subregion (30 μm diameter plug) is selected for advanced imaging
- Dual modality dataset comprised of 149 aligned/paired 2D images from nano-computed tomography (nano-CT) and focused ion beam-scanning electron microscopy (FIB-SEM), with 33.6×33.6 nm pixel size

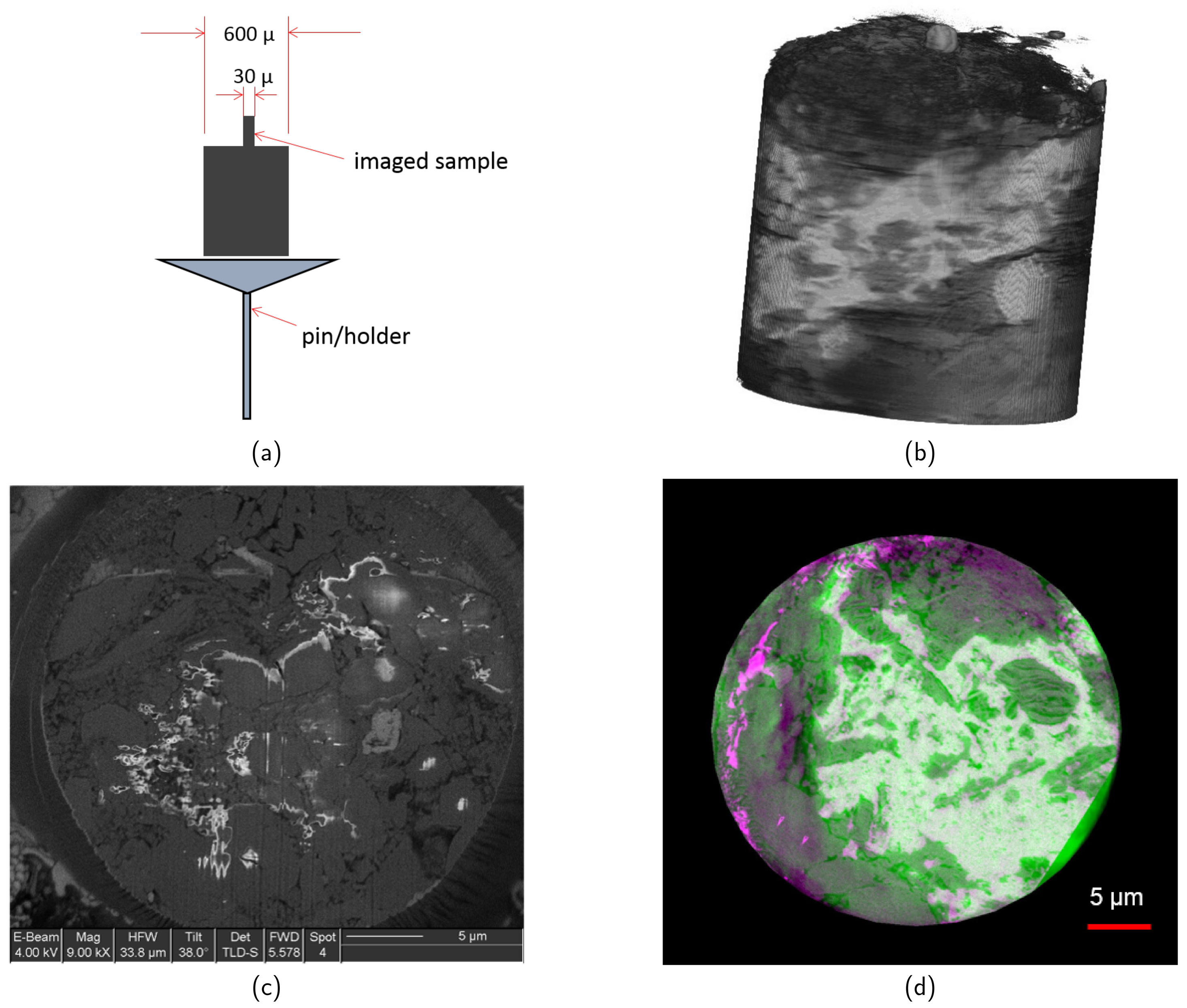

Figure 2: Multimodal imaging dataset. (a) Sample setup, (b) Imaged nano-CT volume of 30 μm diameter plug, (c) Unprocessed FIB-SEM image slice, (d) Example of paired nano-CT/SEM-FIB image slice overlay.

Image Translation Model

- Predicting high-resolution FIB-SEM image from nano-CT input image by combination of image translation, single image super-resolution; apply pix2pix [5] and SR-GAN [7] as baseline models
- 3D volumes required for full characterization, only 2D paired training data available
- Assume that z-gradients sparse in FIB-SEM image volume, use $||\nabla_z \hat{\mathbf{S}}||_1 \leq C \left|\left|\frac{\partial \hat{\mathbf{S}}}{\partial \mathbf{I}}\right|\right|_F^2$ to enforce z-direction continuity with Jacobian regularization

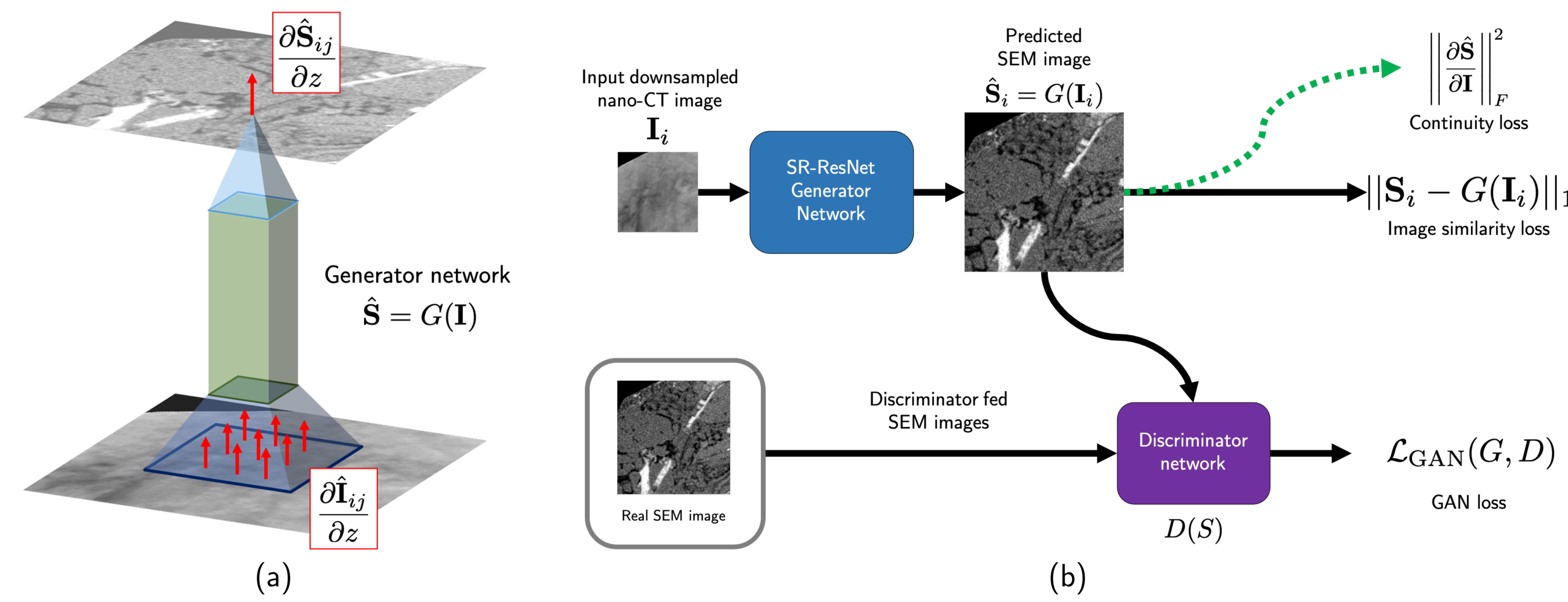

Figure 3: Image prediction model. (a) Depiction of nano-CT image gradients propagating through the generator network to the output image, (b) SR-GAN model with Jacobian regularization term.

Volume Translation Results

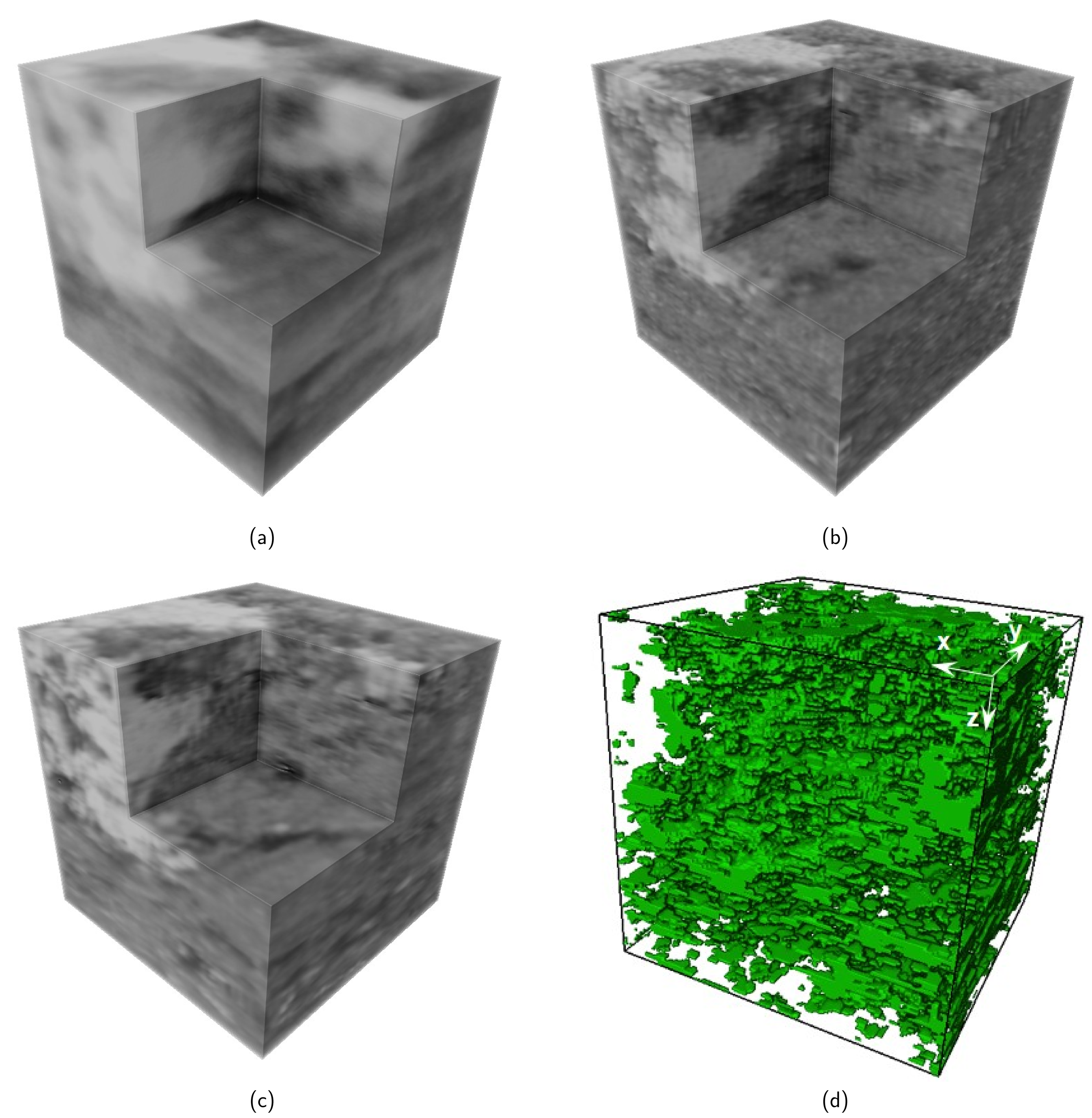

Figure 4: Image volume synthesis results for SR-GAN model. (a) Input nano-CT volume, (b) Synthesized image volume without regularization, (c) Synthesized image with regularization, and (d) Simulation domain for regularized model segmented with thresholding-based segmentation. Lighter shading indicates more dense minerals. Models are trained on paired 2D image slices. During evaluation, $x-y$ image slices are independently passed through 2D-to-2D network and stacked to create image volumes.

Simulation Results

- Simulate flow in z-direction using Stokes equation with finite volume discretization
- Methane introduced at inlet at 1 MPa, 10^{-2} Pa pressure drop in the z-direction, no flow lateral boundary conditions, and single-phase viscosity
- Permeability results show $\mathcal{O}(10^1)$ μd permeability: larger than expected for rock fabric scale

Model	k (d)	ϕ	$\phi_{\text{connected}}$
Original	2.37×10^{-5}	20.7%	18.7%
Regularized	3.01×10^{-5}	18.9%	17.4%

Table 1: Comparison of the flow properties predicted by the original and regularized SR-GAN models. The permeability k, total porosity ϕ, and connected porosity $\phi_{\text{connected}}$ are from PerGeos.

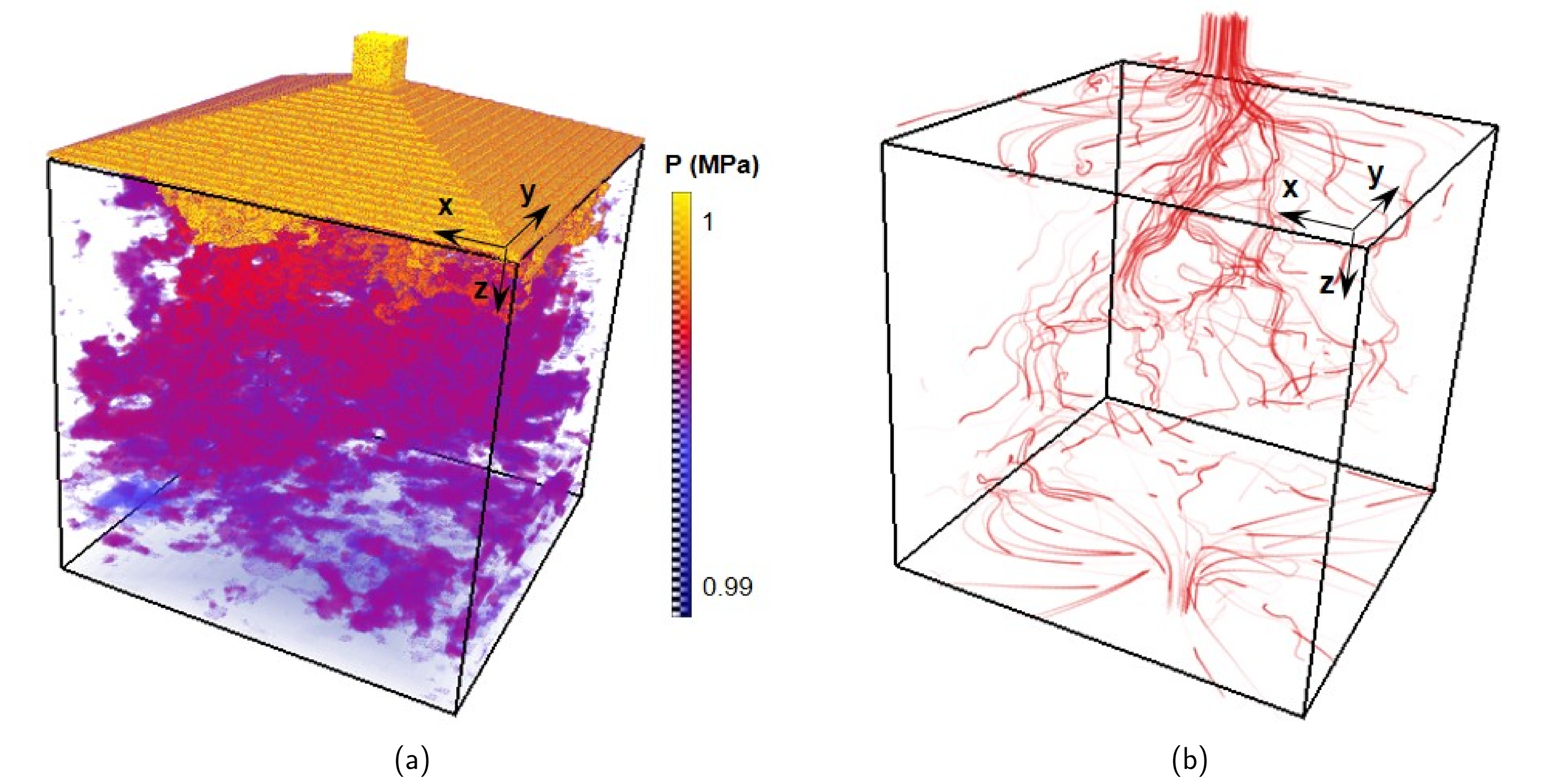

Figure 5: Flow simulation results for the regularized model. (a) Pressure field (including the additional inlet volume) and (b) Flow streamlines. The image translation models enable visualization of flow through the volume and calculation of apparent permeability from nondestructive image data.

Conclusions

- Jacobian regularization term improves volume prediction when only 2D training data is available
- Thresholding-based segmentation of translated images creates suitable simulation domain
- Image translation models allow for visualization of flow with non-destructive image data; simulation results show greater apparent permeability than expected, likely due to assumptions made during segmentation

Future Work

- Further improve $x-z$ and $y-z$ slice continuity, potentially by using a second generator network
- Predict pressure fields directly from non-destructive image data
- Use flow simulation as a prior to improve the image volume prediction

Acknowledgements

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Citations

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