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Data-Efficient Super-Resolution Framework for Enhancing Digital Rock Image Quality Using Transfer Learning

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Abstract Summary

High-resolution digital rock imaging is vital for characterizing pore-scale features in subsurface reservoirs, yet conventional methods remains costly, equipment-dependent, and limited in scalability. To address this, We present an efficient machine learning framework combining synthetic data generation, transfer learning, and data augmentation to train Super Resolution models with minimal real data. Our approach, built upon the SRCNN architecture and enhanced through transfer learning, achieves high-quality reconstructions while reducing reliance on large paired datasets. By incorporating physical constraints into the latent space of the model, we further improve the realism and interpretability of the results. This framework offers a scalable, cost-effective solution for advancing digital rock analysis in energy applications.

Introduction

High-resolution digital rock imaging is crucial for advancing resource extraction in the oil and gas industry, providing insights into the pore-scale structures that govern fluid flow and reservoir behavior (Andrä et al., 2013). While traditional imaging methods such as X-ray Computed Tomography (CT) and Focused Ion Beam Scanning Electron Microscopy (FIB-SEM) offer detailed structural characterization, they are often limited by high costs, complex equipment requirements, and restricted scalability for large datasets or varied lithologies (Andrä et al., 2013). Recent advances in super-resolution (SR) techniques, particularly those driven by deep learning, have opened new possibilities for cost-effective and scalable digital rock image enhancement (Dong et al., 2015; Wang et al., 2020).

In this study, we introduce a novel machine learning framework that addresses the challenge of limited paired training data by leveraging synthetic data generation, transfer learning, and data augmentation. Our approach is built upon the Super-Resolution Convolutional Neural Network (SR-CNN) architecture (Dong et al., 2015), which is pre-trained on synthetic datasets and subsequently fine-tuned using a limited number of real tomography images. This strategy significantly reduces the dependence on large paired data sets, while maintaining high reconstruction quality. Additionally, data augmentation techniques enhance training diversity and model robustness (Shorten and Khoshgoftaar, 2019).

To further improve the physical realism and interpretability of the reconstructed images, we incorporate physics-based constraints into the latent space of the model. This ongoing integration of physics-awareness not only enhances the fidelity of synthetic training data, but also improves the accuracy and generalization of SR results, creating outputs that better reflect real-world pore-scale geometries (Raissi et al., 2019).

In general, the proposed framework presents a scalable and cost-effective solution for high-resolution digital rock imaging, bridging the gap between data-driven methods and physics-informed

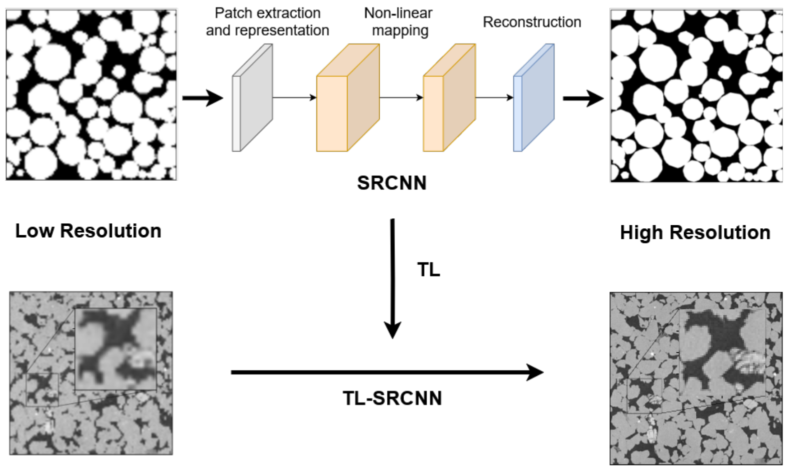

Figure 1: SRCNN and TL-SRCNN architectures

modeling. This contributes to more accurate and accessible reservoir characterization in energy applications.

Model Architecture

We base our super-resolution framework on the SRCNN architecture, a lightweight convolutional neural network designed to learn a mapping from low-resolution to high-resolution images (Figure 1). Its simplicity makes it suitable for evaluating the impact of transfer learning and data augmentation strategies. The network consists of three convolutional layers focused on patch extraction, nonlinear mapping, and reconstruction. This streamlined architecture allows for fast training and inference, making it well-suited for experimentation and adaptation to physics-informed learning frameworks.

Dataset

The model is trained using the DRSRD1-2D dataset (Da Wang et al., 2019), which contains 1000 high-resolution 2D slices of Bentheimer sandstone. These images were downsampled by a factor of 8× to simulate low-resolution inputs, forming paired datasets for supervised learning.

Synthetic Data Generation

To address dataset limitations, we generate synthetic porous media by randomly packing spheres of varying sizes into a 3D volume (Figure 2(a)). Slices of this synthetic 3D rock model are used to create additional high- and low-resolution image pairs (Figure 2(b)). The images are then binarized to distinguish pore and grain regions, simplifying the input and accelerating training (Figure 2(c)). This approach also enables control over grain morphology, allowing simulation of diverse forms such as mineral grains, pebbles, and seashell-like structures(Figure 2(d)).

Transfer Learning Strategy

A base SRCNN model is first trained on the synthetic dataset to learn general pore-scale features. The weights from this model are then transferred to initialize a new model, which is fine-tuned on the

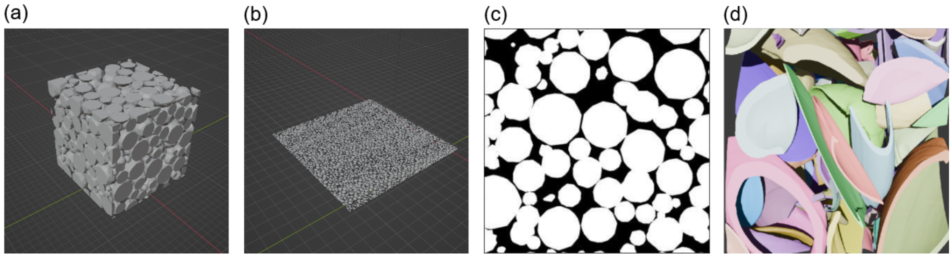

Figure 2: Synthetic generation of packed particle structures for model training

smaller set of real sandstone images. This strategy improves learning efficiency and generalization with limited real data (Figure 1).

VAE-Based Sandstone Generation

To further improve synthetic data realism, we use a Variational Autoencoder (VAE) trained on real rock images to learn latent representation of 3 parameters [x, y, z]. The decoder reconstructs images from these latent variables. By interpolating between nearby latent vectors of real samples, we generate synthetic slices that retain realistic structures while remaining close to the original data distribution (Figure 3).

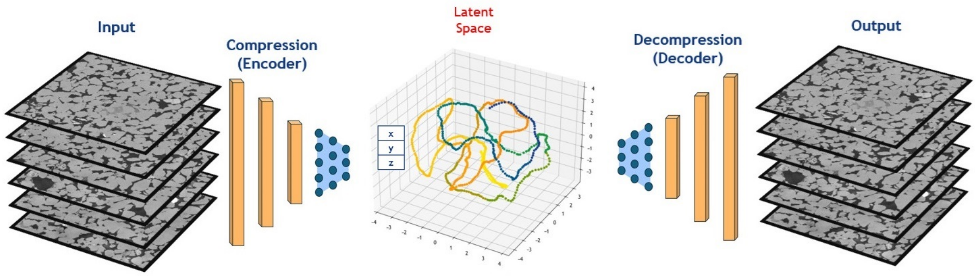

Figure 3: Variational Autoencoder (VAE) Architecture

Data Augmentation

To increase the diversity of training samples, we apply standard augmentation techniques such as rotations, flips, and scaling to real images. This enhances the robustness of the model and helps prevent overfitting, without simply expanding the dataset size.

Results

We evaluate super-resolution performance on images downsampled by a factor of 8. To comprehensively assess reconstruction quality, we use pixel-wise metrics (MSE, PSNR) for image accuracy, LPIPS for perceptual quality, and structural metrics (SSIM, FSIM, EPI) to measure similarity in structure and detail. The baseline SRCNN improves resolution, but TL-SRCNN, pre-trained on synthetic

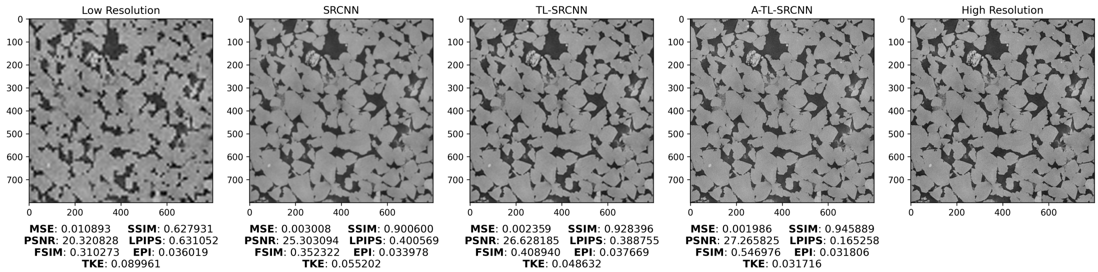

Figure 4: Comparison of models and metrics

and fine-tuned on real data, consistently outperforms it across nearly all metrics, validating the benefit of transfer learning. The A-TL-SRCNN, which enhances variability through feature-level augmentations (not sample quantity), achieves the best results overall in both pixel-wise and perceptual metrics (Figure 4). This aligns with our goal of minimizing reliance on large real datasets. Additionally, we investigate the impact of training set size and find that our models, TL-SRCNN and A-TL-SRCNN, consistently outperform the baseline SRCNN. Both models maintain strong, stable performance even with limited data, demonstrating robustness and effectiveness in data-constrained settings.

Conclusions

This work introduces a novel, cost-effective approach to high-resolution digital rock imaging by utilizing physics-aware, data-driven super-resolution models. By leveraging synthetic data and incorporating transfer learning and data augmentation, we overcome the limitations of traditional imaging techniques, enabling accurate reconstructions with minimal reliance on real data. Future improvements will integrate physics-aware components to generate more realistic synthetic data and further enhance the structural accuracy and quality of super-resolved images. This approach offers a scalable, efficient solution for simulating high-fidelity digital rock models, bridging the gap between machine learning and physics-based methods.

References

Andrä, H., N. Combaret, J. Dvorkin, E. Glatt, J. Han, M. Kabel, Y. Keehm, F. Krzikalla, M. Lee, C. Madonna, et al., 2013, Digital rock physics benchmarks—part i: Imaging and segmentation: Computers & Geosciences, **50**, 25–32.

Da Wang, Y., P. Mostaghimi, and R. Armstrong, 2019, A super resolution dataset of digital rocks (drsrd1): Sandstone and carbonate.

Dong, C., C. C. Loy, K. He, and X. Tang, 2015, Image super-resolution using deep convolutional networks: IEEE transactions on pattern analysis and machine intelligence, **38**, 295–307.

Raissi, M., P. Perdikaris, and G. E. Karniadakis, 2019, Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations: Journal of Computational physics, **378**, 686–707.

Shorten, C., and T. M. Khoshgoftaar, 2019, A survey on image data augmentation for deep learning: Journal of big data, **6**, 1–48.

Wang, Z., J. Chen, and S. C. Hoi, 2020, Deep learning for image super-resolution: A survey: IEEE transactions on pattern analysis and machine intelligence, **43**, 3365–3387.