Generative Adversarial Networks Applied to Noise Remove in Micro-CT for Digital Rock Analysis

Victor Moreira (UFPA)
José Frank Vanzeler Gonçalves (UFPA)
Jose Jadsom Sampaio de Figueiredo (UFPA)
Yana Carolina Pinheiro Machado (UFPA)

Generative Adversarial Networks Applied to Noise Remove in Micro-CT for Digital Rock Analysis

Please, do not insert author names in your submission PDF file.

Abstract

Micro-computed tomography (micro-CT) is essential for microstructural analysis in rocks, offering high-resolution three-dimensional data that is fundamental for petrophysical and geomechanical investigations. However, the presence of noise in the images negatively affects their quality, making it difficult to accurately segment pores and internal structures. This study proposes the use of Generative Adversarial Networks (GANs), adapted from applications in the dental field, to remove noise and highlight structural details in micro-CT images of rocks. The results show that the application of GANs promotes significant improvements in image quality indices, maintaining morphological fidelity and enabling more reliable analyses for reservoir characterization.

Keywords: microtomography, GAN, noise removal, geosciences, deep learning, rock characterization.

Introduction

The analysis of rocks using micro-computed tomography (micro-CT) has become essential in the investigation of petrophysical properties such as porosity, permeability, and pore connectivity Lopes et al. (2012); Neto et al. (2011). This technique provides high-resolution 3D images, which are crucial for reservoir studies and geomechanical characterization. However, acquisition and reconstruction noise often degrades image quality, compromising the accurate segmentation of mineralogical phases and pore spaces, thus affecting interpretative results Jesus and Jr. (2015). Traditional filtering methods, such as Gaussian convolutions, tend to smooth not only the noise but also geological structures that are relevant to the analysis Jesus and Jr. (2015). In this context, advances in deep learning techniques, particularly Generative Adversarial Networks (GANs), have opened new possibilities for digital image enhancement Goodfellow et al. (2014).

With promising results in the biomedical field, where morphological preservation is critical, their potential application to complex geological images is increasingly evident Sorin et al. (2020). This study proposes an innovative methodological adaptation based on the DN-GAN model developed by Chen et al. (2020), originally designed to reduce speckle noise in optical coherence tomography (OCT) images in the biomedical domain. This approach, which leverages generative adversarial networks with contextual encoding blocks and both spatial and frequency domain losses to preserve structural detail, is here transposed to the processing of micro-CT rock images. The goal is to reduce noise in digital rock imagery and enhance fine geological structures, which are fundamental for high-resolution petrophysical analyses. The proposed method aims to remove noise and enhance subtle geological features, contributing to more accurate digital petrophysics. Thus, this work demonstrates how GANs can overcome the limitations of conventional techniques and foster advances in automation and interpretive fidelity in computational geoscience.

Methodology

This study proposes the use of a Generative Adversarial Network (GAN) based on the DenseNet architecture to remove noise in rock microtomography images, with the aim of improving data quality for petrophysical analysis. Initially, the images are pre-processed using techniques such as cropping for data enhancement, greyscale conversion and pixel value normalization, ranging from 0 to 1, following approaches similar to those described by Ronneberger et al.Ronneberger et al. (2015) in image segmentation studies. After this, the necessary hyperparameters for the implementations are defined, such as: Kernel size equal to 3, bacth size equal to 16, learnin rate equal to 0.00004, stride equal to 3 and the optimizer used was Adam. The implementation uses libraries such as PyTorch Paszke et al. (2019) to create the models, with the generator composed of 4 dense blocks Huang et al. (2017) and inside each dense block contains 4 convolutional layers to preserve the rock's texture features. While the discriminator employs a conventional CNN with 8 convolutional layers, for binary classification. The RMSE loss function is adopted for optimization, as suggested by Wang et al. (2004) in image reconstruction contexts, and training is performed using the Adam optimizer Kingma and Ba (2015), ensuring stability during the process.

To evaluate the results, the processed images are compared with noise-free samples using quantitative and qualitative metrics. The pipeline also integrates data augmentation techniques to handle a large volume of images (30,000 samples). Each image is at a scale of 610 x 610 px due to cropping, where each pixel is equivalent to 2.2315 micrometers, for a total of 1,361.215 × 1,361.215 micrometers, ensuring the robustness of the model. The original Isola et al. (2017) methodology is adapted to the petrophysical domain to include segmentation and labeling of matrix and pore regions, which are essential for further analysis. The implementation employs mixed precision techniques Micikevicius et al. (2018) to speed up training, while data normalization follows the standards set in previous geological image processing studies Wildenschild and Sheppard (2013). Preliminary results demonstrate the approach's effectiveness in reducing noise and preserving porous structures, validating its applicability in digital rock studies. These steps are described in the flowchart in Figure 1.

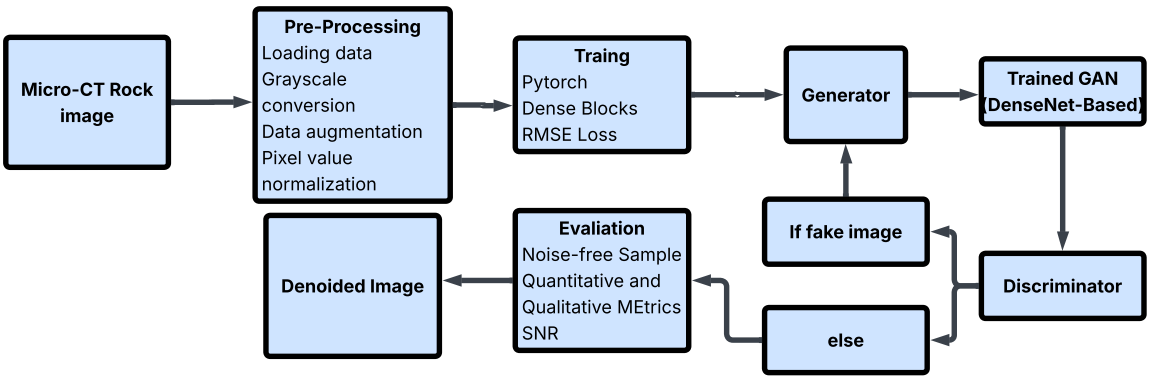

Figura 1: flowchart showing the steps taken in the methodology.

Results and Discussions

The results of this work were obtained using two classic quantitative metrics for image quality assessment: peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM), as suggested by

Ledig et al. (2017) in the context of image reconstruction with generative adversarial networks. Thus, after developing the generated image, this technique was implemented to evaluate the effectiveness of the proposed technique during the methodology. By applying the metrics, it was possible to obtain similarity degrees of 81% and a signal-to-noise ratio of 22.78 dB.

The image in Figure 2 shows the processing steps until reaching the final result, where we start from the binarized image 2a). Immediately after, noise is added, and the type of noise is shown in Figure 2b).

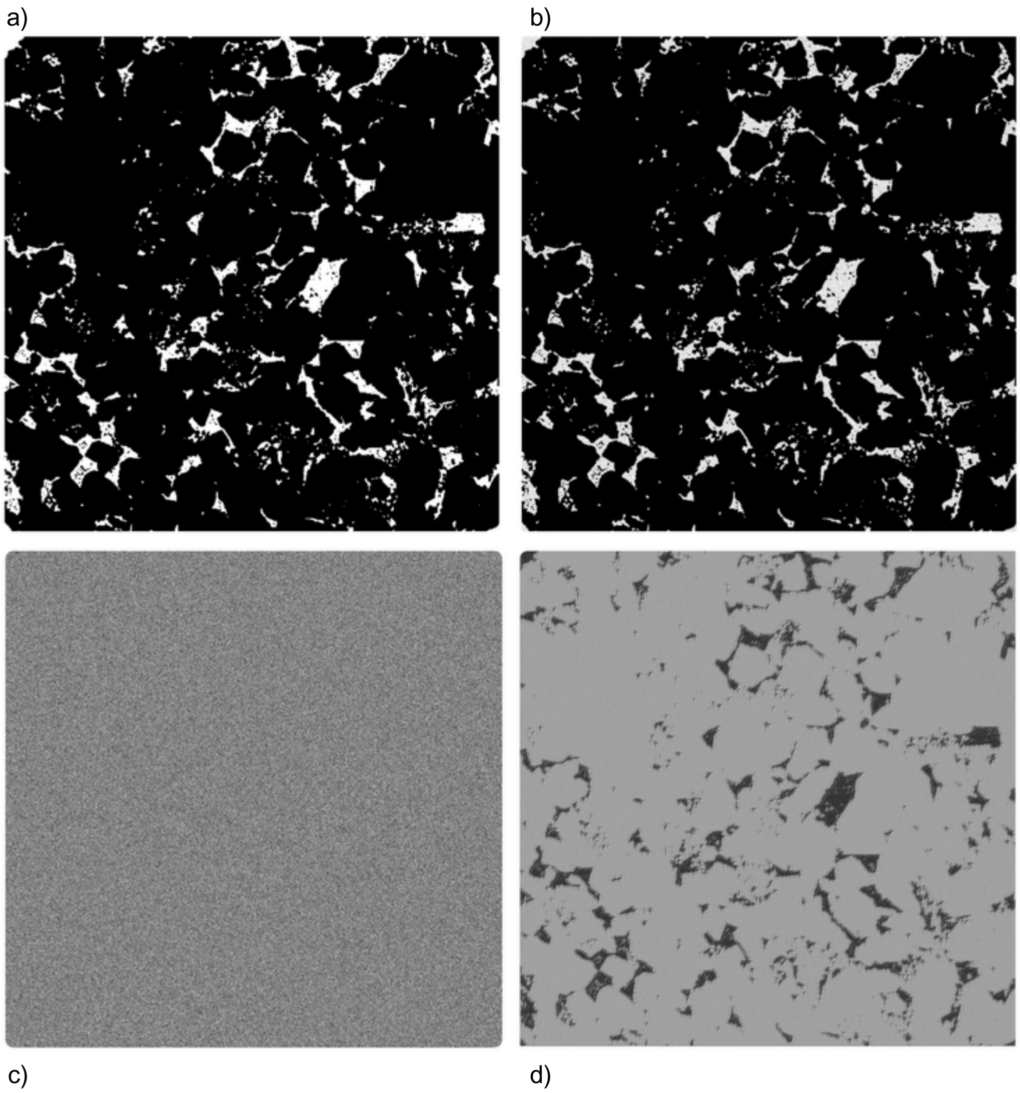

Figura 2: a) Original image; b) Image with random noise; c) Gaussian noise from 0 to 5%; d) Generated image. The images are a total of 1,361.215 × 1,361.215 micrometers.

Generative Adiversarial Networks are approaches that can be used to handle qualitative and quantitative information accurately. These techniques take into account the nature of precision in data generation, which makes them effective for manipulating knowledge efficiently. Using the DNGAN method for noise removal in microCT images proved to be a significant approach for digital rock analysis studies. This technique was able to identify certain types of noise in specific types of rock and remove them with good efficiency. Thus proving to be a method of great importance for data processing, identification and pattern recognition for future projects.

Referências

Chen, Z., Z. Zeng, H. Shen, X. Zheng, P. Dai, and P. Ouyang, 2020, Dn-gan: Denoising generative adversarial networks for speckle noise reduction in optical coherence tomography images: Biomedical Signal Processing and Control, **55**, 101632.

Goodfellow, I., J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, 2014, Generative adversarial nets: Presented at the Advances in Neural Information Processing Systems.

Huang, G., Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, 2017, Densely connected convolutional networks: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 4700–4708.

Isola, P., J.-Y. Zhu, T. Zhou, and A. A. Efros, 2017, Image-to-image translation with conditional adversarial networks: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 1125–1134.

Jesus, E. O., and R. C. Jr., 2015, A utilização de filtros gaussianos na análise de imagens digitais: Presented at the Congresso Nacional de Matemática Aplicada e Computacional (CNMAC).

Kingma, D. P., and J. Ba, 2015, Adam: A method for stochastic optimization: International Conference on Learning Representations (ICLR).

Ledig, C., L. Theis, F. Huszár, J. Caballero, A. Cunningham, A. Acosta, A. Aitken, A. Tejani, J. Totz, Z. Wang, and W. Shi, 2017, Photo-realistic single image super-resolution using a generative adversarial network: arXiv preprint arXiv:1609.04802.

Lopes, A. P., et al., 2012, Análise tridimensional de rochas por meio de microtomografia computadorizada de raios x: Geociências (UNESP).

Micikevicius, P., S. Narang, J. Alben, G. Diamos, E. Elsen, D. Garcia, B. Ginsburg, M. Houston, O. Kuchaiev, G. Venkatesh, et al., 2018, Mixed precision training: arXiv preprint arXiv:1710.03740.

Neto, J. M. R., et al., 2011, A microtomografia computadorizada de raios x integrada à petrografia: Revista Brasileira de Geociências.

Paszke, A., S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, T. Killeen, Z. Lin, N. Gimelshein, L. Antiga, et al., 2019, Pytorch: An imperative style, high-performance deep learning library: Advances in Neural Information Processing Systems, 8024–8035.

Ronneberger, O., P. Fischer, and T. Brox, 2015, U-net: Convolutional networks for biomedical image segmentation: International Conference on Medical Image Computing and Computer-Assisted Intervention, Springer, 234–241.

Sorin, V., et al., 2020, Creating artificial images for radiology applications using gans – a systematic review: Academic Radiology.

Wang, Z., A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, 2004, Image quality assessment: from error visibility to structural similarity: IEEE Transactions on Image Processing, **13**, 600–612.

Wildenschild, D., and A. P. Sheppard, 2013, X-ray imaging and analysis techniques for quantifying pore-scale structure and processes in porous media: Advances in Water Resources, **51**, 217–246.