Stochastic 3D rock reconstruction using GANs

Andrea Valsecchi [a,b] and Sergio Damas [b,c]

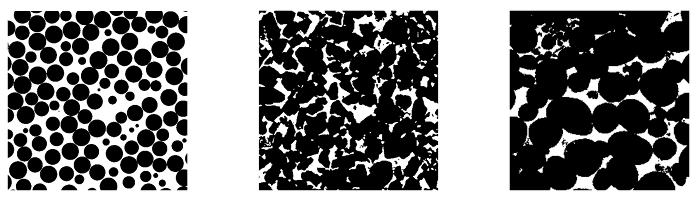
a Panacea Cooperative Research, Ponferrada, Spain

b Andalusian Research Institute in Data Science and Computational Intelligence, University of Granada, Spain

c Dept. of Software Engineering, University of Granada, Spain

1. Introduction

The behaviour of a fluid moving through sedimentary rock is controlled by the rock's pores structure. The study of such structures in porous media plays a key role in many scientific applications [1]. Using micro computed tomography (micro-CT) scanners, it is possible to acquire high-resolution 3D images of a porous media at the scale of individual pores. The following are 2D cross-sections of such images for three kind of media.



2. Stochastic reconstruction

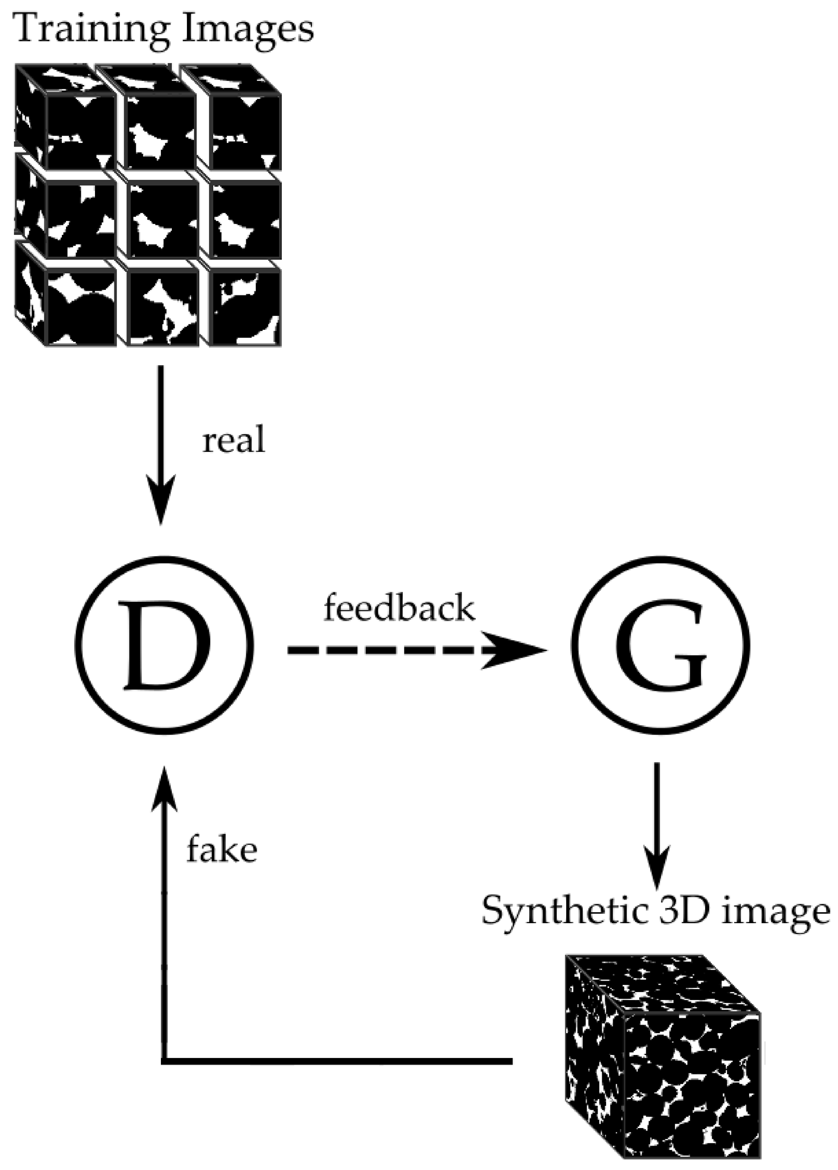
To evaluate the variability of morphology in a specific rock type, a large number of rock samples is required. Using micro-CT scans is unfeasible, due to the time and cost required for the acquisition. This motivated the development of *reconstruction* methods that, when provided with few rock scans, aim at generating novel rock images exhibiting the same kind of pore structures. Statistical reconstruction methods are based on measuring some spatial statistical properties of the training images and producing novel images having similar values of these properties. The reconstruction of 300^3 voxels media requires tens of hours of computation per realization.

3. GANs for rock reconstruction

Recently, researchers have investigated the use of GANs for the reconstruction of three-dimensional porous media [3]. The work shows that GANs are a viable method for stochastic reconstruction of three types of rocks. In addition to being accurate, the generation of new images is extremely fast after the training phase (roughly 24 hours on their hardware), avoiding the drawback of traditional methods. We have recently introduced a novel method for 2D-to-3D reconstruction of the structure of porous media by applying GANs [4].

4. Methodology

We employed the design of [3] as starting point and incorporated some more recent components. Both the discriminator network D and the generator network G work on 3D images.



The input layer is densely connected to a 32-channel, three dimensional image of size 32^3, which is later upsampled to 64^3. The rest of the layers alternate between batch normalization, activation and 3x3x3 3D convolution. The input of the discriminator is a 64^3 3D image. The following layers can be grouped into four blocks made of 3D convolution, activation using LeakyRELU, dropout and batch normalization layers. The last layer uses dense connections and a sigmoid activation function. Both networks were trained using the Adam optimizer with a learning rate of 0.2×10^{-5}.

5. Evaluation

While objective, quantitative evaluation of generative models is notoriously difficult, in the case of porous media there are some well-established morphological criteria [2].

Two-point statistics

The two-point probability function of the pore phase is the probability that two points x and $x + r$, separated by a lag vector r, are both located in pore phase P.

$$S_2(r) = \mathbf{P}(x \in P, x + r \in P) \text{ for } x, r \in \mathcal{R}^3 \quad (1)$$

Morphological measures

The morphological characteristics of the void-solid interface of a porous medium can be characterized using the Minkowski functionals: the porosity ϕ, the specific surface area S_V and the Euler characteristics χ. The porosity is simply the ratio of void volume to the bulk of the volume of the sample. The specific surface area is the amount of surface per unit of volume, i.e.

$$S_V = \frac{1}{V} \int dS \quad (2)$$

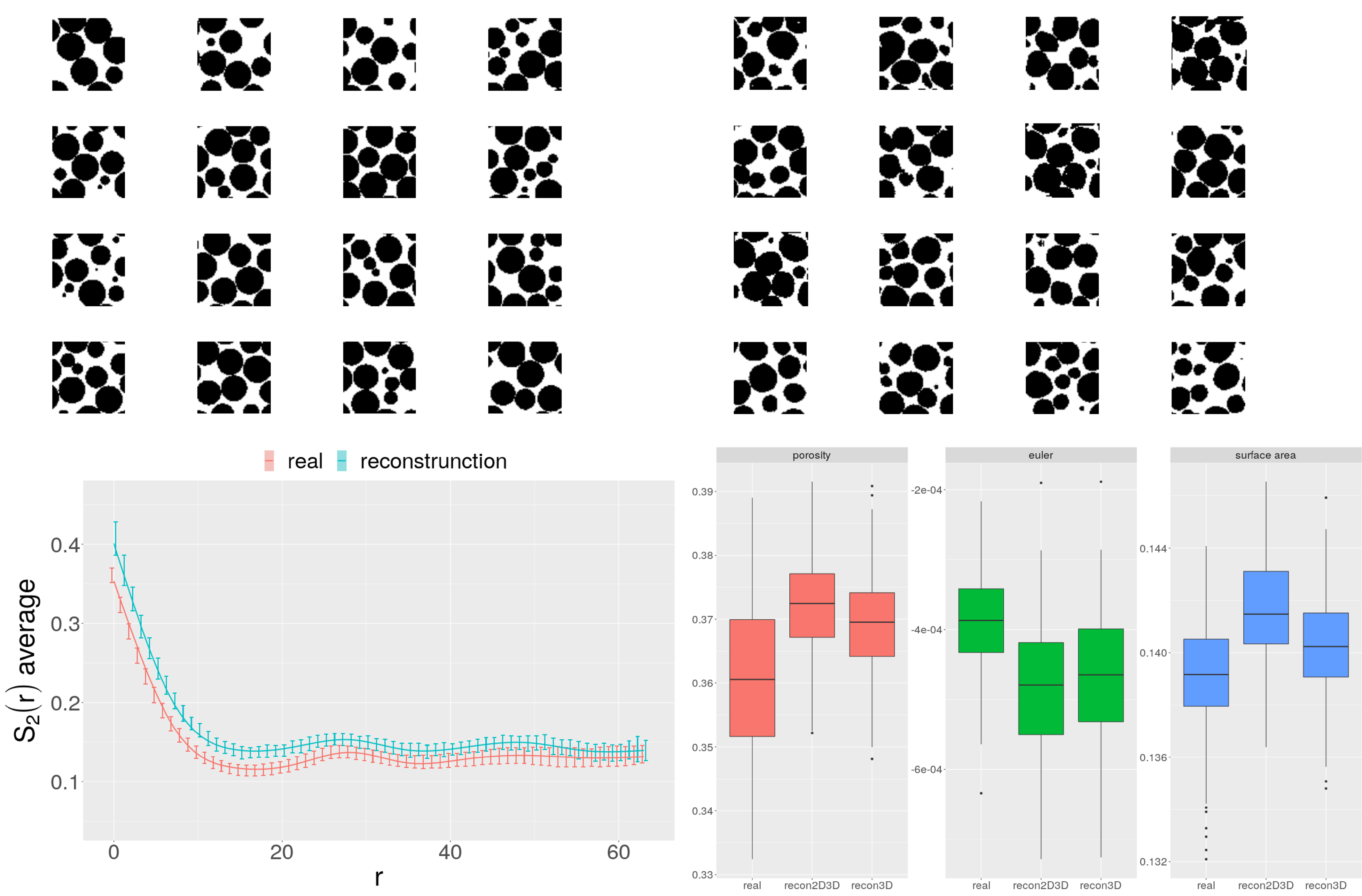
The specific surface area controls the speed of adsorption and dissolution processes. Finally, the Euler characteristics is defined as

$$\chi = \frac{1}{4\pi V} \int \frac{1}{r_1 r_2} dS \quad (3)$$

where r_1, r_2 are the principal radii of curvature of the void-solid interface.

6. Results

Beadpack rock – real vs reconstructed



Two-point correlation and Minkowski functionals in original (real) and reconstructed images

7. Conclusion

Our GANs-based method can reconstruct three-dimensional images of porous media at different scales that are representative of the morphology of the original images. Furthermore, the generation of multiple images is much faster than classical image reconstruction methods.

8. References

[1] Martin J. Blunt, Branko Bijeljic, Hu Dong, Oussama Gharbi, Stefan Iglauer, Peyman Mostaghimi, Adriana Paluszny, and Christopher Pentland. Pore-scale imaging and modelling. *Advances in Water Resources*, 51:197 – 216, 2013. 35th Year Anniversary Issue.

[2] Klaus R. Mecke. Additivity, convexity, and beyond: Applications of minkowski functionals in statistical physics. In Klaus R. Mecke and Dietrich Stoyan, editors, *Statistical Physics and Spatial Statistics*, pages 111–184, Berlin, Heidelberg, 2000. Springer Berlin Heidelberg.

[3] Lukas Mosser, Olivier Dubrule, and Martin J. Blunt. Reconstruction of three-dimensional porous media using generative adversarial neural networks. *Phys. Rev. E*, 96:043309, Oct 2017.

[4] A. Valsecchi, S. Damas, C. Tubilleja, and J. Arechalde. Stochastic reconstruction of 3D porous media from 2D images using generative adversarial networks. *Neurocomputing*, 399:227–236, 2020.