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Morphology Decoder: Untangling Heterogeneous Porous Media Texture and Quantifying Permeability and Capillary Pressure by Semantic Segmentation

Thursday, 2 June 2022 09:25 (15 minutes)

Determining porous media physical properties, like permeability and capillary pressure, in heterogeneous porous media, like carbonate rock, is one of the most challenging tasks for scientists in the digital rock physics domain. One of these challenges is the untangling of the heterogeneous texture. Another challenge is the image's resolution, which controls the visible details of the texture. The third challenge is the size of the representative sample, where the resolution and size form an inverse relationship. At the same time, the fourth challenge is the pore network simulation, which holds lots of assumptions with error accumulation. Finally, the fifth challenge is the high computation power and related high power consumption and long calculation time. Therefore, we propose a solution for untangling the heterogeneous texture: the morphology decoder of image resolution-independent, sample size-independent, simulation free, and machine learning-driven [1-86].

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Time Block Preference

Time Block A (09:00-12:00 CET)

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