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Super resolution reconstruction of μ-CT image of rock sample using neighbour embedding algorithm

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HIGHLIGHTS

- An image-embedding method is applied to improve the resolution of μ-CT.
- High resolution SEM image is used to extract high- and low- image patch pairs.
- Image patch pairs are used in supervise the reconstruction of μ-CT image.

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ABSTRACT

X-ray computed tomography (μ-CT) is considered to be the most effective way to obtain the inner structure of rock sample without destructions. However, its limited resolution hampers its ability to probe sub-micro structures which is critical for flow transportation of rock sample. In this study, we propose an innovative methodology to improve the resolution of μ-CT image using neighbour embedding algorithm where low frequency information is provided by μ-CT image itself while high frequency information is supplemented by high resolution scanning electron microscopy (SEM) image. In order to obtain prior for reconstruction, a large number of image patch pairs contain high- and low- image patches are extracted from the Gaussian image pyramid generated by SEM image. These image patch pairs contain abundant information about tomographic evolution of local porous structures under different resolution spaces. Relying on the assumption of self-similarity of porous structure, this prior information can be used to supervise the reconstruction of high resolution μ-CT image effectively. The experimental results show that the proposed method is able to achieve the state-of-the-art performance.

1. Introduction

A three-dimensional (3D) porous structure is the premise of quantitative evaluation of transport properties of reservoirs at pore-scale. There are two options to obtain 3D inner structure of porous media, deterministic method including various imaging devices and mathematical reconstruction [1].

Deterministic method directly uses various imaging devices such as X-ray computed tomography (μ-CT), scanning electron microscope (SEM) and Focussed ion beam scanning electron microscopy (FIB/SEM) to scan the rock sample to generate the realistic inner structure digitally. Among these imaging devices, μ-CT is seen to be the most direct and convenient approach to provide us with the 3D porous structure of rock samples [2], however its low resolution of few microns hampers its ability to probe the sub-micro pore-throat structures which have critical effect on fluid transport [3–5].

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Therefore, μ-CT image is always insufficient to describe some tight rock samples such as silty sandstone, limestone and shale. FIB/SEM has emerged as an effective way to acquire the 3D porous structure of rock sample with nano-scale resolution, but the field of view (FOV) of FIB-SEM image is too small to capture the heterogeneity of most rock samples [6]. With SEM image it is possible to generate images with various resolution ranges from nano-scale to micro-scale corresponding with a FOV ranges from micro- to milli-scale. The SEM image is, however, 2D and fails to describe 3D structural features. Due to the high cost as well as limitations of resolution or FOV, a set of mathematical reconstruction methods are proposed to generate 3D porous structure digitally.

Because the reconstruction of porous structure of rock samples pursuits that the statistic properties of reconstructed porous media is consistent with training image rather than reproduce structure realistically, stochastic reconstruction methods are the mainstream of rock reconstruction during the last decades such as Gaussian random field reconstruction method, processed based reconstruction, Markov Chain Monte Carlo scheme (MCMC) and multiple-point statistic (MPS) reconstruction [2,7–18]. The basic ideal of these stochastic reconstruction algorithms is to capture statistical prior from training image, usually 2D high resolution images such as SEM images or optical microscopy images, and then using this prior knowledge to supervise the reconstruction of 3D high resolution porous structure. Although these methods have been used universally for porous structure reconstruction, the resulting images do not always capture the long-range connectivity of pore space, namely for low porosity and particular media [19]. In theory, MCMC and MPS method has potential to reproduce the heterogeneity and connectivity of target structures, but that needs extremely large training images and large template which is impractical in reconstruction. In addition, these algorithms focus on generating a 3D porous structure based on the prior knowledge extracted from 2D training image directly. Along with the universally use of μ-CT, a hybrid strategy is proposed to generate more deterministic 3D image in which the low frequency information is obtained from μ-CT image directly and then supplement high frequency content extracted from high resolution 2D images. Okabe and Blunt [2] introduced a method to recover the small features lost in low resolution μ-CT image by combining 2D SEM images with 3D low resolution μ-CT image. In this approach macro-pores are identified by μ-CT while micro-pores are generated by MPS reconstruction method based on SEM image. Then the two images are superimposed to obtain the final image with an improved image quality. This hybrid strategy is extended to a multiresolution and multiscale modelling to address the problems associated with computational cost and multiscale features reproduction [20–22]. In this method, low resolution image is applied to reconstruct the large-scale features in shale sample and high resolution 2D images are used to reconstruct the nano-scale structures. Then, the multiscale pore network is obtained by overlying the micro and macro 3D models. In some cases, the macro scale reconstruction can be skipped if a 3D macro image is gettable directly. Except to these stochastic reconstruction algorithm, a promising choice to improve the resolution of μ-CT images is applying super resolution reconstruction (SRR) method which widely used in medicine, astronomy and military field which can enhance the resolution of low resolution tomographic images (greyscale images) directly. Unlike the image reconstruction in medicine and astronomy which supplement the lost high frequency information from other low resolution images, the reconstruction of μ-CT image of rock sample can get high resolution SEM image as training image directly. These high resolution SEM images provide more realistic detailed information of porous structures that provide better performance in SRR.

As one of the most active research areas, various SSR methods have been proposed in literatures. In recent years more and more researchers are interested in features of self-similarity because it has the ability to preserve maximum level of information [23]. The self-similarity based super-resolution method depends on the observation that small scale structures tend to repeat themselves throughout an image [24,25]. Chang, Yeung and Xiong [26] used the self-similarity phenomena and extended the approach by adopting the neighbour embedding based super-resolution algorithm. Later, Chan, Zhang, Pu and Huang [27] introduced a filtering process for reducing number of patch pairs, thereby reducing computation time. Yang, Wright, Huang and Ma [28], Zeyde, Elad and Protter [29] introduced sparse representation to further reduce computation effort.

In this paper, we propose a neighbour embedding super-resolution reconstruction algorithm (NESRR) to enhance the resolution of μ-CT image. The remainder of this work is organized as follows. In next section, a $180 \times 180 \times 180$ μm^3 μ-CT image of shale sample is applied as an example to illustrate the procedures of NESSR from intensity calibration to self-similarity reconstruction. And then, a reserved SEM image is used to estimate the quality of reconstruction.

2. Preprocess of images

2.1. Sample preparation

A $2 \times 2 \times 3$ mm^3 size shale sample is used to demonstrate the process of NESRR method. Firstly, the whole sample was imaged at a resolution of $2 \times 2 \times 2$ μm^3 on the Australian National University X-ray μ-CT facility to capture the large scale heterogeneity of the sample (see Fig. 1(a)). Note that at this resolution, obtained μ-CT image is just available to roughly characterize the geometrical and distribution features of micro-scale objects in the shale, such as micro-pores, micro-fractures, kerogen and clay minerals, etc. Then, one surface of the cuboid shale sample is polished and scanned by SEM equipment, and the obtained SEM image has a size of 2×3 mm^2 with a resolution of 330×330 nm^2/pixel which detect the more detailed information of shale sample (see Fig. 1(b)). Finally, the registration work between SEM section and μ-CT