Automatic Fracture Identification using X-ray Images

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SUMMARY

Coal seams are characterised as highly anisotropic and heterogeneous geological formations with extremely low porosity and permeability at reservoir conditions. Despite the advances in digital rock physics with the introduction of micro-computed tomography (micro-CT) over the last decade, characterising coal remains a challenge. One such challenge is processing micro-CT images to extract fracture features such as aperture, length and orientation which cannot be directly resolved using micro-CT images. We aim to present an automated fracture identification technique using grayscale images obtained from micro-CT imaging of coal. This technique uses pattern recognition and computer vision to recognise the presence of a fracture, even those that are below the resolution of micro-CT data. This approach will then generate probability maps of fractures while alleviating the dependence on a single segmented image. Later, a three-dimensional fracture system for coal will be developed from the above approach, and this can be used as an input for flow simulations and estimation of permeability. Overall, this technique will enable us to develop multiple realisations of the coal fracture system using a probabilistic method and prove to provide an alternative path to resolve the problems caused by manual segmentation.

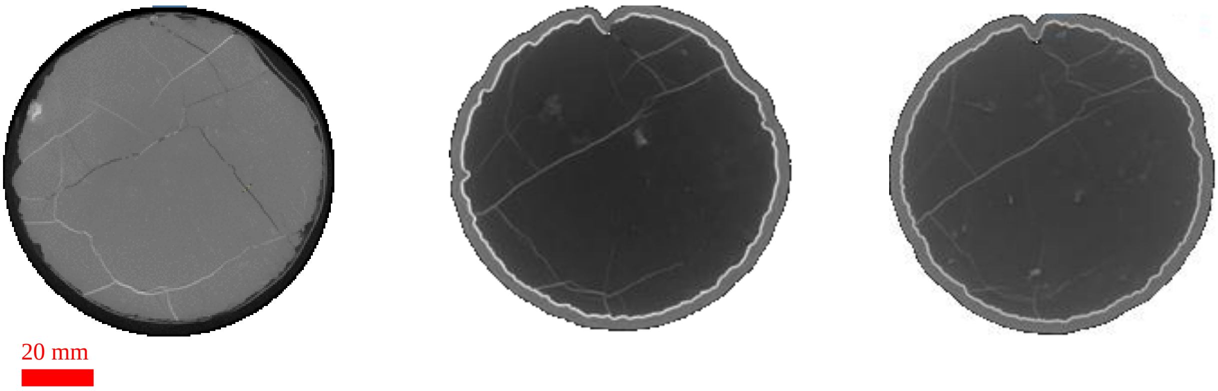
Key words: Coal seam, Fracture, Permeability, Micro-CT imaging

INTRODUCTION

Coal seams exhibit a dual porosity system characterised by a complex network of the perpendicular face and butt cleats and a low porosity matrix with methane adsorbed on its surface (Moore, 2012). This system can surpass the capacity of an equivalently sized sandstone reservoir to produce natural gas by almost seven times (Thakur et al., 2014). However, extraction of such large amounts of coalbed methane (CBM) requires detailed characterisation of the fracture. For this purpose, micro-computed tomography (micro-CT) is used. These images assist in visually analysing the fractures. Each of these fractures is described by their orientation, length and aperture (Mostaghimi et al., 2017). Furthermore, these high-resolution micro-CT images are converted to segmented images to distinguish between matrix, pores and fractures. While segmentation works well for sandstones, the same is not true for coal micro-CT images. There is a significant trade-off between sample size and image resolution (Mostaghimi et al., 2017), i.e. imaging a large core sample might result in poorly resolved fractures. In short, manual image segmentation might not capture these fractures (Saxena et al., 2017) especially for coal imaged under high-stress regimes. Segmentation process may introduce errors in fracture properties that subsequently affect petrophysical analyses. To eradicate this problem arising from image resolution and segmentation of micro-CT images, we aim to present an automated fracture identification workflow using grayscale images. This fracture identification workflow is based on pattern recognition and computer vision techniques which have reached milestone achievements in remote sensory imagery and medical sciences. For our case, we will analyse the intensities of each pixel in the grayscale image. Later, our results will produce probability maps of fractures and provide an estimation of their length, orientation and aperture size. This technique will help to alleviate the dependence on a single segmented image which would otherwise ignore most of the poorly resolved fractures.

METHOD AND RESULTS

Micro-CT images of an Australian coal sample with resolution of 36 micrometres (μm) and size of 2400×2400×1596 voxels are obtained at different pressures (Figure 1). To recognise the fractures from these images, we propose to use a texture-based pattern recognition technique called Gray-Level Co-occurrence Matrix (GLCM) proposed by Haralick et al. (1973). GLCM identifies the spatial relationship between neighbouring pixels using statistical analysis, i.e. it recognises the frequency with which a particular pattern of grey-level intensities occur in the specified analysis window (Haralick et al., 1973). In particular, we calculate attributes such as energy, entropy and contrast for a specific analysis window of the grayscale image. Later, a texture image is created based on each of these attributes. These texture images highlight different aspects of the coal grayscale image and hence, can then be used to identify fractures as they exhibit a specific pattern which distinguishes them from the coal matrix. Once, these patterns are recognised, we will then use computer vision to reconstruct probability distributions of these fractures in 2D and later in 3D. This reconstruction will be based on fracture length, aperture and orientation. Overall, when compared to a single segmented image from which fracture geometries are studied, this approach will provide us with an advantage to understand the effect of possible fracture scenarios on flow simulations.



(a) (b) (c)

Figure 1: Micro-CT images of coal at (a) ambient pressure, (b) confining pressure of 500 psi and (c) confining pressure of 1000 psi. Each of these images has resolution of 36 micrometers and size of 2400×2400×1596 voxels.

CONCLUSIONS

A pattern recognition and computer vision based fracture identification technique is proposed. This technique uses GLCM and Haralick's statistical measures to recognise fractures. This approach is directly applicable to grayscale images and enables better visualisation of fractures which are poorly resolved by micro-CT images. Moreover, this method alleviates the dependence on segmented images which are biased and also, provides a reliable solution to the trade-off between sample size and image resolution especially for coal. Overall, this robust technique can be used to identify fractures and describe its properties such as aperture, length and orientation by creating probability maps.

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