

# Constructing Three-Dimensional Digital Rock of Continental Shale with Multi-Mineral Components Using Machine Learning Segmentation Algorithms

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## Research significance

- Continental shales, characterized by well-developed laminations and high clay content, present challenges in sample preparation and fluid saturation, making conventional rock physics experiments difficult to conduct<sup>[1]</sup>.
- Continental shale reservoirs exhibit numerous nanopores, indistinct clay particle boundaries, and small openings in bedding planes, complicating the segmentation of shale sample X-ray CT scan images.
- Digital rock physics technology has evolved as a vital complement to these experiments.

## Multi-mineral component 3D digital rock

### Samples characteristics

- The sample selected in this paper is one Mixed shale, numbered R1.
- The porosity of the cores was determined by helium method.
- The mineral content of the core was analyzed by XRD experiment.

Tab.1 XRD sample constituent content

sample	Gas measurement of porosity%	quartz%	k-feldspar%	albite%	calcite%	ankerite%	clay minerals%	pyrite%	feldspathic minerals%	carbonate minerals%
R1	5.753	27.6	1.3	22.1	2.4	5.5	37.7	3.4	51	7.9

### Mineral test

- The sample conducted X-ray Computer Tomography (CT) scans tests with scanning resolutions of 1.35 $\mu$ m.
- Conduct Quantitative Evaluation of Minerals by Scanning Electron Microscopy (QEMSCAN) tests with scanning resolutions of 1 $\mu$ m.
- Conduct Multi-spectral Automated Petrographic System (MAPS) tests with scanning resolutions of 10nm.



Fig.1 CT scans image

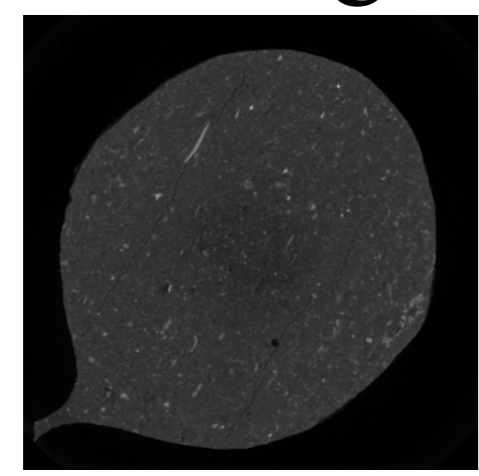


Fig.2 MAPS image

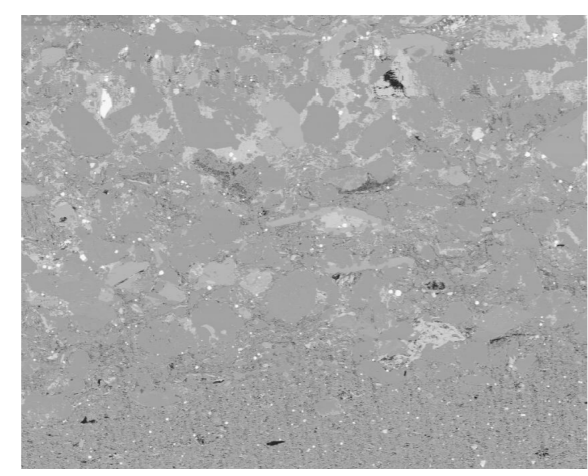
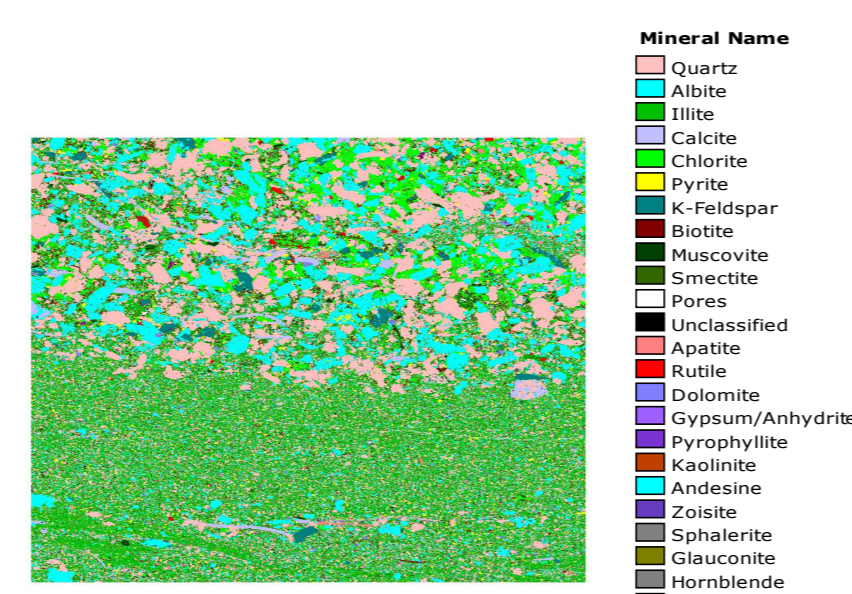


Fig.3 QEMSCAN image



## The machine learning image segmentation algorithm

- Combining QEMSCAN images with CT scans, the grayscale ranges for different mineral components were identified.
- A machine learning image segmentation algorithm was then employed to divide the CT scan grayscale images into six components: pores, organic matter, clay minerals, feldspathic minerals, carbonate minerals, and pyrite.

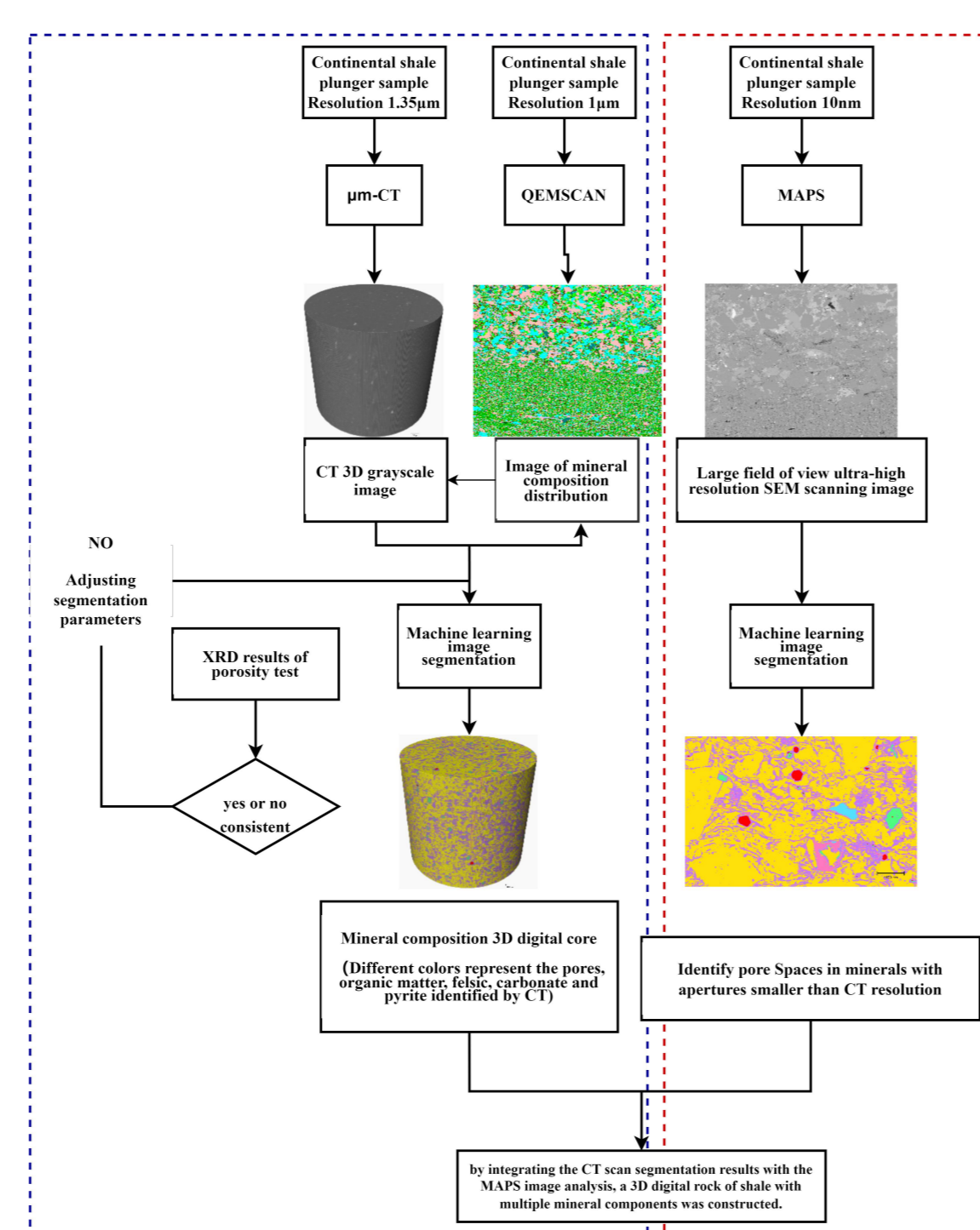


Fig.4 3D digital rock flow chart

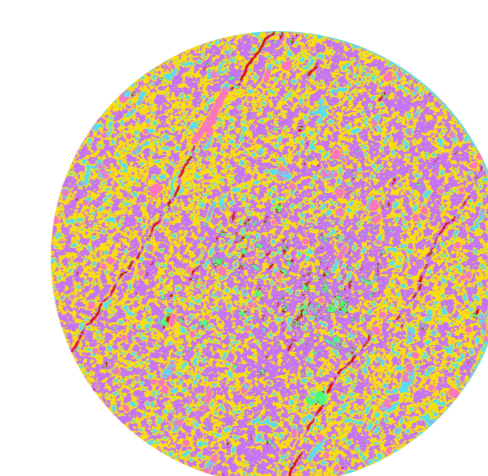
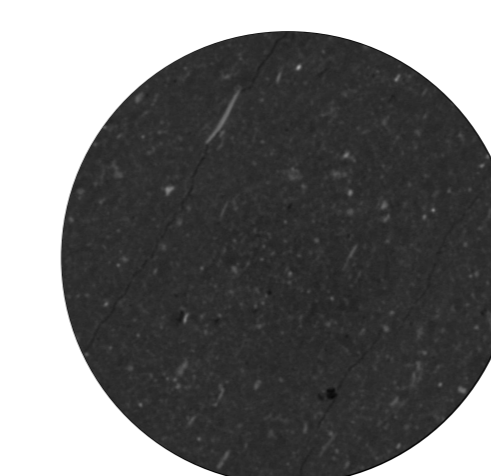
- The machine learning segmentation algorithm was applied to the two-dimensional MAPS images of the shale sample endfaces to identify pore spaces smaller than the CT resolution in the carbonate minerals of organic matter and clay minerals and to calculate the surface porosity.
- By integrating the CT scan segmentation results with the MAPS image analysis, a 3D digital rock of shale with multiple mineral components was constructed.

## The segmentation results of the machine learning

- The segmentation results of the X-ray CT scan images indicate that the content of the main mineral components aligns with X-ray Diffraction (XRD) analysis results. The porosity identified in CT images is significantly lower than the helium porosity of the samples.

Tab.2 The machine learning segmentation sample constituent content

sample	porosity%	organic%	feldspathic minerals%	carbonate minerals%	clay minerals%	pyrite%
R1	1.18	1.69	48.43	8.03	37.34	3.34



- pore
- organic
- feldspathic minerals
- clay minerals
- carbonate minerals
- pyrite

Fig.5 The machine learning segmentation images

- By combining this with MAPS images, it is determined that the CT-identified pores are large pore spaces between grains and bedding fractures.

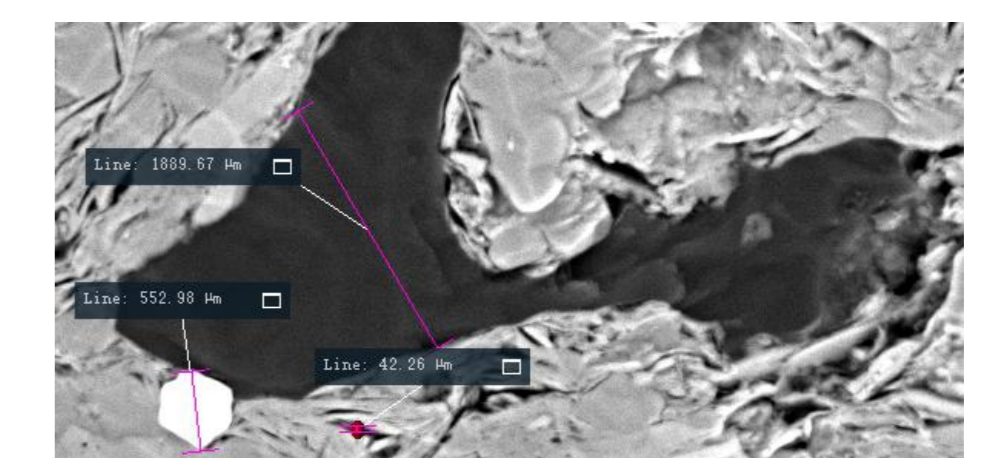
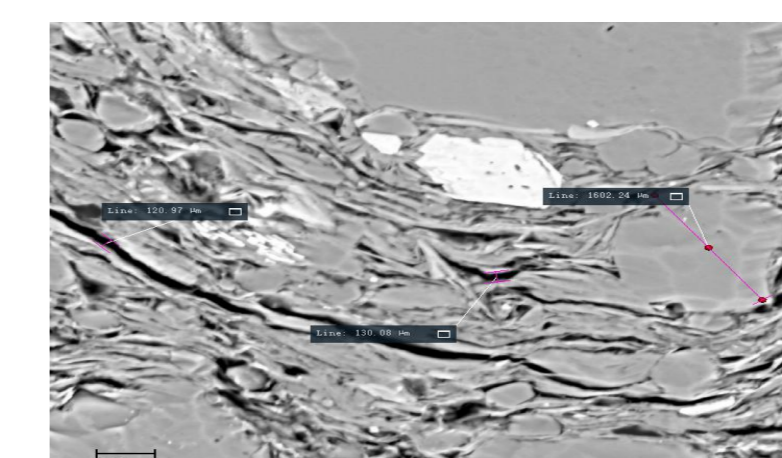


Fig.6 Clay inter-crystalline pores and mineral size comparison

## Conclusion

- The machine learning segmentation algorithm provides higher accuracy in identifying the boundaries of the skeleton and pores compared to traditional grayscale threshold segmentation algorithms.
- It more accurately identifies unidirectionally extended bedding fractures.
- The total porosity of the multi-mineral component 3D digital rock aligns closely with the gas-measured porosity, providing an accurate pore scale model for quantitative analysis of the microstructure of continental shale and numerical simulation of its rock physical properties.

## References

- [1] WANG Pengwei, ZHANG Yaxiong, LIU Zhongbao, CHEN Xiao, LI Fei, HAO Jingyu, WANG Ruyue. Microfracture development at Ziliujing lacustrine shale reservoir and its significance for shale-gas enrichment at Fuling area in eastern Sichuan Basin. Natural Gas Geoscience[J], 2021, 32(11): 1724-1734 doi:10.11764/j.issn.1672-1926.2021.05.008