

PRF# 59363-DNI9

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Project Title: Microscale Connectivities of Wetting and Non-Wetting Fluid Phases in Liquid-Rich Shales and Their Effects on the Propagation of Diffusion Front

Accomplishments of Budget Period #1

Accomplishment #1: Developed machine-learning (ML) assisted SEM-image segmentation workflow to locate and delineate various constituents of shale samples (fig. 1). Generalization capability of the ML-assisted segmentation was tested on two distinct shale formations, namely Wolfcamp and Barnett shales. One of the most important evaluation for any data-driven model is its generalization capability. When trained and tested on SEM images from the same formation, the overall segmentation performance in terms of F1 score is 0.95 and 1 for the outer-region and inner-region pixels, respectively. For purposes of generalization, the outer-region and inner-region pixels of pore/crack and organic/kerogen in shales are segmented at average F1 scores of 0.90 and 0.95, respectively. Pixel Intensity, Gaussian blur, Sobel operator, and local minimum, maximum and mean around the pixels are the most important features for the proposed segmentation. Random forest is the best suited classifier for this task. Hyperparameter optimization of the random forest ensures the generalization.

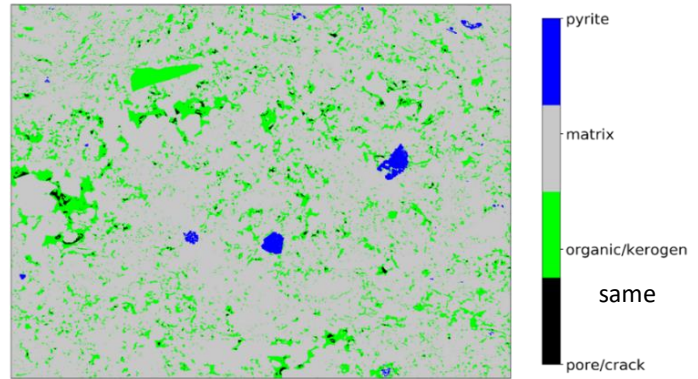


Fig. 1: ML-assisted segmentation of 4 distinct constituents present in a SEM image of organic-rich shale sample, namely pore/crack, organic/kerogen, matrix and pyrite components.

Accomplishment #2: Developed and tested five statistical formulations/metrics to quantify the connectivity of material constituents captured in microscopy/tomography. Six types of synthetic binary images with different levels of connectivity are generated for the evaluation of the five connectivity-quantification metrics, namely geobody connectivity index, Euler’s number, indicator variogram, connectivity function, and fast-marching traveltime distribution. Euler’s number increases from -5.68 to 292.77, which indicates the connectivity decreases from Type 1 to 6, which is consistent with visual examination. Fast-marching method simulates the evolution of boundaries and interfaces. Mean of fast-marching traveltime distribution (fig. 2, bottom left) for the phase of interest exponentially decreases from 35 to 1 as connectivity decreases from Type 1 to 6. Mean of connected distance based on connectivity function (fig. 2, bottom right) exponentially decreases from 140 to 2 as connectivity decreases from Type 1 to 6. These metrics can be applied on SEM images of shales to quantify the connectivity of constituents (fig. 2). Non-scalar metrics such as indicator variogram (fig. 2, top right) exhibit directionality and can quantify the anisotropy in connectivity. Scale-dependent metric, such as indicator variogram and connectivity function, is function of separation distance that quantifies the scale of connectivity, ranging from local to global connectivity.

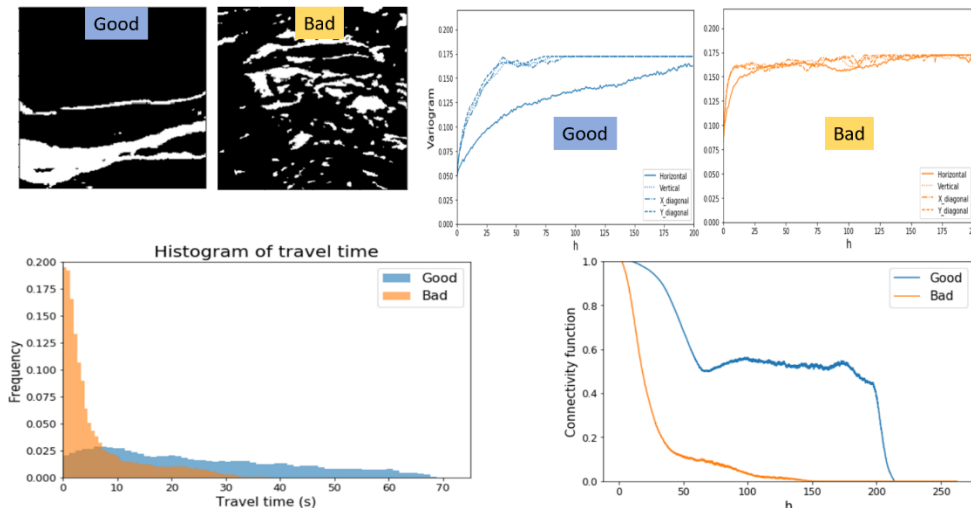


Fig. 2: (top left) Two 200µm×200µm SEM images of shale samples, representing well connected (good) and poorly connected (bad) samples. Top right figures show the indicator variograms in horizontal, vertical, and two diagonal directions. Bottom left shows the traveltime distributions. Bottom right shows the connectivity functions.

Accomplishment #3: The abovementioned metrics were used to quantify the microscale connectivity of various fluid phases/constituents in the segmented CT scans of a porous geological sample (fig. 3) undergoing sequential fluid injection at five chronological stages, namely Case 1: initial brine saturated state; Case 2: post first oil injection; Case 3: post first water flooding; Case 4: post first gas injection; and Case 5: post second water flooding. The entire CT scan of the porous sample contains 3000 slices. Due to the sequential injection of various fluid types, the microscale connectivity of each fluid phase/constituent undergoes dramatic change from one stage to the other (fig. 3). A visual inspection to evaluate the changes in fluid phase connectivity and to determine the connectivity of each fluid phase in each slice of the entire CT scan is an arduous task. To improve the accuracy and to speed up the connectivity quantification in the CT scan of the porous sample, we first segmented the 3000 CT-scan slices; following that, the five above-mentioned metrics (figs. 4 & 5) were applied on the segmented CT-scan slices.

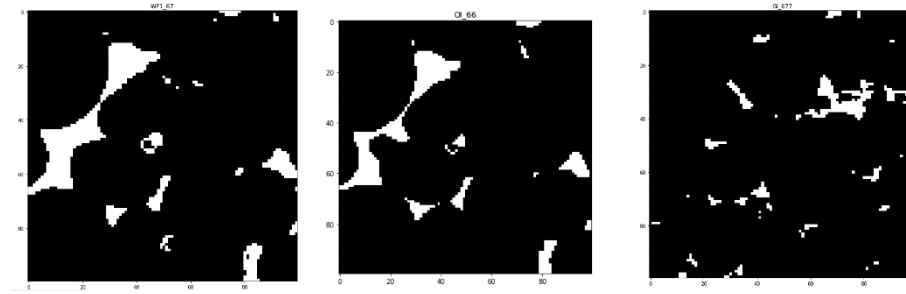


Fig. 3: 2D binary, segmented CT-scan slices exhibiting highest connectivity of (left) water phase for Case 1; (middle) oil phase for Case 2; and (right) gas phase for Case 4.

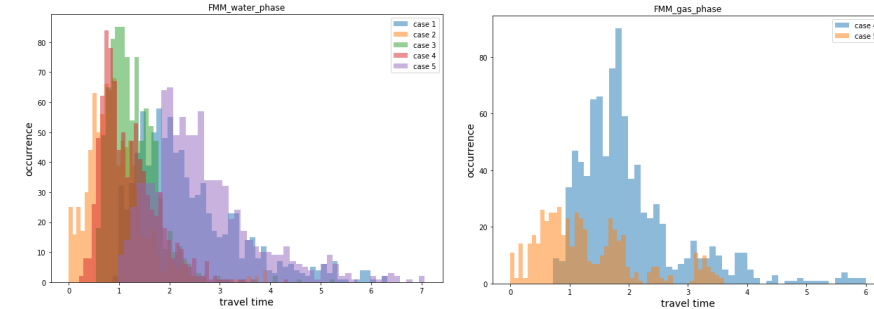


Fig. 4: Fast-marching traveltimes distribution for the (left) water phase and (right) oil phase in the entire sample (comprising 3000 2D CT-scan slices) at various stages of sequential fluid injection.

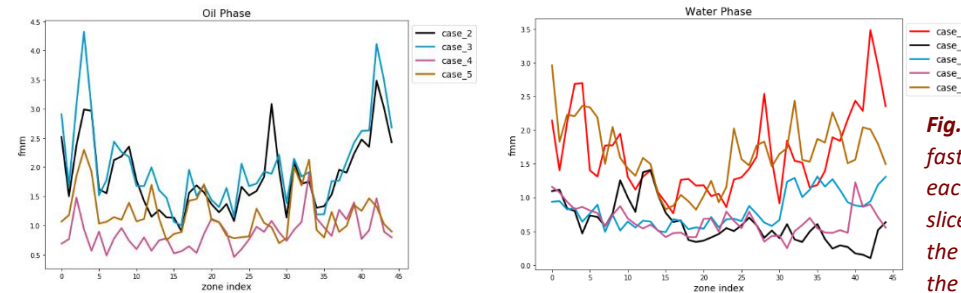


Fig. 5: Variations in the mean fast-marching traveltimes for each zone (containing 70 slices per zone) as function of the length of the sample and the stages of sequential fluid injection.

Goals for the Budget Period #2

- Apply Markov random fields to quantify the microscale connectivity of fluid phases in porous materials.
- Apply the segmentation and connectivity quantification methods on fluid-filled liquid-rich shale samples.
- Explain the physical nature of the microscale fluid-phase connectivity in liquid-rich shale samples.
- Demonstrate the effects of fluid-phase connectivity on the propagation of pressure and diffusion fronts.

Impact of the research on PI’s career: This research helped PI generate preliminary findings that led to the prestigious DOE Early Career Award (2018). PI was invited by several institutes/agencies to present this research. Several oil and gas companies are interested in applying these methods for improved subsurface characterization.

Impact of the research on graduate student’s career: This research has helped the 2 students publish two papers in Fuel Journal (IF: 5) and IEEE Geoscience and Remote Sensing Letters (IF: 2.9). The research helped the students write two chapters for the book: “Machine Learning for Subsurface Characterization”. This experience will help the students find summer internships related to the use of data-driven methods for petroleum research/engineering.