Abstract

A thorough knowledge about rock properties is crucial for economic oil and gas exploration. Unconventional resources are known to exhibit multi-scale and highly heterogeneous pore structure. Imaging techniques are widely used to visualize and study rock properties. Due to limitations in imaging technology, less than 1% of a rock sample area can be sampled and studied at high resolution. Obviously, relevancy and representativeness of sampling area as well as obtained rock properties are often considered unreliable. We present an in-house developed technology that combines imaging techniques with machine learning to characterize multi-scale rock properties. The technology is based on the understanding that a rock consists of building blocks, i.e. fabrics, intermixed spatially at various scales. Detailed knowledge of all fabrics at its representative scale will lead to an improved characterization of the rock sample. A fabric possesses a set of properties, e.g. porosity, fraction of organic matter, pore size distribution and others. Unsupervised machine learning is used to learn about fabrics present in a sample. It also recommends optimum sub-sampling areas for smaller-scale higher resolution image acquisition and properties upscaling. The required resources in this approach are several orders of magnitude lower than acquiring mosaics of small-scale images covering a similar area at the large scale.

We apply the present technology to acquire images and characterize pore properties of rock samples from the Eagle Ford, Marcellus, and Bakken units. The rock sample area is approximately 0.5 × 0.5 [mm] with a resolution of 244 [nm]. Small-scale images with an area of approximately 30 ×18 [micron] with a resolution of 10 [nm] are used to characterize pores within fabrics. The upscaled pore properties and fractions of organic matter are compared with that derived from small-scale mosaic covering a similar area. The comparison shows a very good agreement confirming the accuracy and reliability of the present technology. The present work demonstrates a novel approach to characterize multi-scale rock properties using machine learning technique. This is a step towards bridging knowledge from pore scale (where hydrocarbon lives) to the reservoir scale (where production takes place) for economic oil and gas exploration.
Characterize Millimeter-Scale Unconventional Rock Using Micron-Scale Sample Imaging & Machine Learning

R. Sungkorn, A. Morcote, G. Carpio, T. Cavanaugh, J. Toelke
Ingrain Inc.
Unconventional Resources – Unconventional Information

- Seismic
- Well logging
- Well cores
- Plugs
- Cuttings

kilometers

micron
Unconventional Resources – Unconventional Information

Seismic

Well logging

Well cores

Plugs

Cuttings

kilometers

micron
Unconventional Resources – Unconventional Information

Scale where oil is produced

- Seismic
- Well logging

Scale where oil lives

- Well cores
- Plugs
- Cuttings

kilometers to micron
Unconventional Resources – Unconventional Information

Seismic

Well logging

Well cores

Plugs

Cuttings

kilometers

micron

INGRAIN
Unconventional Resources – Unconventional Information

- Seismic
- Well logging
- Well cores
- Plugs
- Cuttings

kilometers
micron
Multi-Scale Imaging

Well cores

Cuttings

2D SEM mm-scale

2D SEM μm-scale

3D SEM

Field of View

10000

1000

100

10

1
Rock Properties Upscaling

- Well cores
- Plugs
- Cuttings
- 2D SEM mm-scale
- 2D SEM µm-scale
- 3D SEM

Field of View

- 10000
- 1000
- 100
- 10
- 1

Scale:
- Well cores: 0,0 - 1
- Plugs: 0,1 - 1
- Cuttings: 1 - 10
- 2D SEM mm-scale: 10 - 100
- 2D SEM µm-scale: 100 - 1000
- 3D SEM: 1000 - 10000
Two-Scale Characterization

Well cores

Cuttings

Plugs

2D SEM mm-scale

2D SEM µm-scale

3D SEM

Field of View

10000

1000

100

10

1
2D SEM mm-scale

Eagle Ford

1 mm
2D SEM mm-scale

Eagle Ford

2D SEM µm-scale

1 mm
2D SEM mm-scale vs. 2D SEM µm-scale
Building Blocks

Rock feature

Rock fabric

Rock texture

Increased complexity
Building Blocks

- Rock feature
- Rock fabric
- Rock texture

Increased complexity
Real vs. Digitalized Image

Resolved feature

Unresolved feature

Pixel / voxel resolution
2D SEM mm-scale

Eagle Ford

2D SEM µm-scale

1 mm
2D SEM mm-scale: Fabrics

Eagle Ford

2D SEM µm-scale

1 mm
Fabrics on 2D SEM mm-scale

2D SEM μm-scale
2D SEM mm-scale: Fabrics & Samplings

Eagle Ford
2D SEM mm-scale: Fabrics & Samplings

Eagle Ford

1 mm
Fabrics 2D SEM mm-scale

2D SEM μm-scale
Fabrics 2D SEM mm-scale

2D SEM µm-scale

Fabric A

Fabric B

Fabric M

Fabric N
Mosaic Properties (≈100 2D μm SEM images)
Fabrics-Based Upscaled Properties (~10 2D µm SEM images)
Rock Porosity
Rock Organic Fraction

![Graph showing the relationship between Mosaic Property and Fabric-Based Prediction](image)

- Blue square: Mathew
- Triangle: Burbank
- Circle: Armstrong
- Diamond: GOFF
Rock Pore Associated with Organic (PAOM) Fraction

![Graph showing the relationship between Mosaic Property and Fabric-Based Prediction for Mathew, Burbank, Armstrong, and GOFF samples.](image-url)
2D SEM mm-scale

Fabrics on 2D SEM mm-scale

Multi-Scale Statistics
Multi-Scale Statistics

Low Resolution

High Resolution

\[ I_{Low\ Res,\ fabric\ j} = \sum (\alpha_i I_{Material,i} + \varepsilon_i) + \varepsilon \]
Multi-Scale Statistics

$$I_{Low\ Res,fabric\ j} = \sum (\alpha_i I_{Material,i} + \varepsilon_i) + \varepsilon$$