Seismic elastic double-beam characterization of faults and fractures for CO$_2$ storage site selection

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FINANCIAL ASSISTANCE
FUNDING OPPORTUNITY ANNOUNCEMENT

Department of Energy (DOE)
Office of Fossil Energy (FE)

EMERGING CO$_2$ STORAGE TECHNOLOGIES: OPTIMIZING PERFORMANCE
THROUGH MINIMIZATION OF SEISMICITY RISKS AND MONITORING
CAPROCK INTEGRITY

Funding Opportunity Announcement (FOA) Number: DE-FOA-0002401
Announcement Type: Amendment 1
CFDA Number: 81.089
AOI 1a - Fault Detection, Characterization, and Hazard Assessment.

Goals and Objectives for Gigatonne injection

(a) CO2 injection

Super critical CO2

aquifer

M = \mu A d

Crystalline basement

\sigma_1 \rightarrow \sigma_1

1 2 3 4 5
Methodology

• Develop 9-component (9C) elastic double-beam method for small-scale fracture characterization (self validating)
• Develop large-scale fault detection method
• Synthesis:
  – fractures/faults in sedimentary layers and basement;
  – Stress
  – Estimating earthquake hazards
  – Estimating fluid pathways to basement faults
• Field data test: 9C seismic dataset from Wolf Springs in Central Montana
Objectives budget periods (BP)

- **BP 1.** Fault detection and fracture characterization in the basement using synthetic 9C surface seismic data (Year-1)

- **BP 2.** Fault detection and fracture characterization in the basement using field 9C surface seismic data (Year-2)

- **BP 3.** Determination of fault stress state and fault activation potential (Year-3)
Task/Subtask Breakdown

Task 2.0 - Fault detection and fracture characterization in the basement using synthetic 9C surface seismic data

This task will be in Year-1 which is the budget period 1. The work will focus on synthetic dataset based on a model with dimensions similar to the Wolf Springs field data.

- **Subtask 2.1** – (UH/LANL/Vecta) Model building based on central Montana (M1-M3): Build a 3D elastic model using the Wolf Springs field geometry.

- **Subtask 2.2** – (UH) Multicomponent synthetic seismic data modeling (M4-M6): Using the model and the locations of the sources and receivers in the field data, UH will run their elastic finite-difference code to generate the synthetic datasets. The computation will be done on PI’s group cluster.

- **Subtask 2.3** – (LANL) Migration imaging (M7-M9): LANL will conduct P-P, P-S, S-P, and S-S imaging on the synthetic dataset.

- **Subtask 2.4** – (LANL) Machine learning fault detection (M10-M12): LANL will detect faults on P-P, P-S, S-P, and S-S images of the synthetic dataset.

- **Subtask 2.5** – (UH) Fracture characterization using elastic double beam (M10-M12)
Roadmap
Why another method for fracture characterization?

• Can seismic migration see the small-scale fractures?
  • No.
Fractures: vertical; 9m height; fracture compliance $1\times10^{-10}$ m/Pa

Motivational example: fractures are hard to see

Finite difference modeling: Coates and Schoenberg (1995)
Hard to see fractures in traditional seismic migrated images
How does the seismic double-beam method characterize small-scale fractures
From point sources to localized wave packet
From point sources to localized wave packet
From point sources to localized wave packet
From point sources to localized wave packet
From point sources to localized wave packet
From point sources to localized wave packet
From point sources to localized wave packet
Interference pattern \(\rightarrow\) fractures

Directional wave incidence

Interference pattern (observation)

Frac parameter inversion

Fractured reservoir
- Fracture orientation
- Density
- Compliance \(\rightarrow\) fluid permeability (Petrovitch et al., 2013)
Field seismic data (9C) in Montana
Vertical vibroseis
Fractures and Basement faults

(a) PP image

(b) SP image
Build the synthetic elastic model from the field data
P-wave velocity model from the field Vecta data
Shear-wave velocity model from the field Vecta data
Density model from the field Vecta data
Synthetic Vp model with:
- a normal fault
- vertical artificial fracture sets
- small fractures extracted from field data image

Fractures extracted from the field data image

Normal fault

vertical artificial fractures at different depths
Two coexisting sets

Z: 1200-1700 m

Z: 1000-1200 m

Z: 1600-1750 m

vertical artificial fractures
Sources:
X: 2800:125:6550 m
Y: 2100:125:4850 m
Total: 31*23=713

Receivers:
X: 2800:35:6615 m
Y: 2100:35:4900 m
Total: 110*81=8910

Both Source and receivers are at surface
Modeled common-shot gathers at one location with different types of source.
Source wavelet: 20 Hz Ricker
Explosive source
Single force: X
Single force: $Y$
Single force: Z
Fracture detection results using
The Seismic Double-Beam method
At three depths (1100 m, 1400 m and 1650 m) from frequencies 15 Hz, 20 Hz, 30 Hz and 40 Hz
3D view of detected fractures
Example of DB images
Depth 1100 m: **Has fractures**

15 Hz

20 Hz

30 Hz

Geometry
Depth 1400 m: Has fractures

SS/HC: f 15 Hz tx 4100 ty 4500 inline 450 xline 410

SS/HC: f 20 Hz tx 4100 ty 4500 inline 450 xline 410

SS/HC: f 30 Hz tx 4100 ty 4500 inline 450 xline 410

Geometry
Depth 1400 m: Has fractures

Azim=085
Spa=156
Amp=2.5mx10
Hc = 1.36e+61

Target 207:
-x=3860
y=29700

Azim=075
Spa=188
Amp=5.65e-10
Hc = 1.1e+62

Depth 1400 m: Has fractures

Azim=085
Spa=156
Amp=2.5mx10
Hc = 1.36e+61

Target 207:
-x=3860
y=29700

Azim=075
Spa=188
Amp=5.65e-10
Hc = 1.1e+62

SS/HC: f 15 Hz tx 3600 ty 3700
inline 370 xline 360

SS/HC: f 20 Hz tx 3600 ty 3700
inline 370 xline 360

SS/HC: f 30 Hz tx 3600 ty 3700
inline 370 xline 360

Geometry

Previous -
Next +
Save
Depth 1650 m: Has fractures

SS/HC: f 20 Hz tx 6500 ty 4400 in-line 440 inline 650

SS/HC: f 30 Hz tx 6500 ty 4400 in-line 440 inline 650

SS/HC: f 40 Hz tx 6500 ty 4400 in-line 440 inline 650

Geometry
No consistent focused “bright spot”
Depth 1400 m: No fracture

Azim=117
Span=150
Amp=2.38e-09
Hc = 9.58e+00

Azim=075
Span=150
Amp=5.83e-10
Hc = 1.46+02
Depth 1400 m: No fracture
Next steps: discrete fracture network using Machine learning
Elastic double-beam neural network (DBNN) machine learning

The architecture of our fully-connected neural network including two hidden layers.
Large-scale faults detected using LANL’s new NRU

Nested Residual U-shaped convolutional neural network (NRU)
Summary

• Year-1 focused on synthetic model and data tests

• UH, LANL, and Vecta Oil and Gas ltd. worked together and built a 3d seismic model: Vp, Vs, density and spatially varying fracture networks including conjugate fracture sets

• We modeled 3d 9-c shot gathers

• We applied the double-beam method on the modeled datasets and found
  – If there are fractures, DB can invert for the true fractures
  – If there is on fracture in the model, DB reports ‘no fracture’
  – Different frequencies give consistent results → DB method is self verifying

• In the Gigaton CO2 injection scenario, our methods could be extremely useful in providing information: permeable fluid flow pathways, stress state, and earthquake hazards
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