FE0009260: ADVANCED JOINT INVERSION OF LARGE DATA SETS FOR CHARACTERIZATION AND REAL-TIME MONITORING OF CO₂ STORAGE SYSTEMS

Enhancing Storage Performance and Reducing Failure Risks under Uncertainties

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Stanford University

U.S. Department of Energy National Energy Technology Laboratory
Carbon Storage R&D Project Review Meeting
Developing the Technologies and Infrastructure for CCS
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Acknowledgements

- Co-PI: Eric Darve
- Post Doc: Amalia Kokkinaki
- Research Assistants: Judith Li, Hojat Ghorbanidehno, Ruoxi Wang
- Former Research Assistant: Sivaram Ambikasaran
- Our LBNL Collaborators: Jens Birkholzer, Quanlin Zhou, Xiaoyi Liu, Keni Zhang
- Program Manager at DOE: Karen Kluger
Outline

• Role in the program
• Objectives
• Contributions to date
• Ongoing work
• Road ahead
Current needs in CCS

Support decision making for best design and control of CO$_2$ injection and storage operations

- This involves:
  - Process simulation of complex, large, multiphase systems.
  - Dynamic monitoring with instrumentation providing near-continuous, but noisy datasets.
  - Assimilation of data of multiple types.
  - Uncertainly quantification and risk assessment.
Our objective

- Develop, test, and apply advanced algorithms for high resolution estimation of subsurface properties and CO$_2$ transport and provide uncertainty estimates.

- Geostatistics and Kalman Filtering
- Multiphysics at a “fine” scale

- Fast Linear Algebra
- High Performance Computing

- Sound statistical framework
- State of the art forward simulators

- Large scale systems
- Large datasets
- Millions of unknowns
- Near-continuous monitoring data
- Best available technology
- Near-continuous monitoring data
Project overview 1/2

Advance Methodologies

• Static inversion → Geostatistical inversion → Characterization

• Dynamic inversion → Kalman Filter → Real-time CO₂ monitoring
• Evaluate developed methods for realistic CCS examples
  • Synthetic cases
    • Three-dimensional, heterogeneous, real-sized domains
  • Real cases
    • Frio-I pilot test and In Salah site
Static inversion using $H$ matrices


- Harnessing the hierarchical structure of matrices used to describe geospatial correlation, we can dramatically reduce the cost of matrix operations.
Static inversion
Principal Component Geostatistical Approach

- Hydraulic tomography application to large-scale system: 750 m x 1000 m, 3x10^6 unknowns
- < 50 terms needed!
- Inversion completed in less than two hours, with a storage cost of roughly 1.5 GB

Dynamic monitoring - CSKF

- Compressed State Kalman Filter

- Matrix factorization of the covariance using a fixed basis leads to smaller matrices and faster computations, with minimal loss of accuracy of the inversion algorithm.

Joint estimation of permeability and CO₂ saturation using measurements of CO₂, pressure, and water production rates.
Dynamic monitoring - HiKLF


- Hierarchical Kalman Filter for quasi-continuous data assimilation
- Reduction of computation cost from $O(m^2)$ to $O(m)$  \( m \): # unknowns

CO₂ monitoring with seismic travel times

\[ \Delta S_p \times 10^{-4} \text{ s/m} \]

<table>
<thead>
<tr>
<th>Number of unknowns, ( m )</th>
<th>Time (sec)</th>
<th>Storage (MB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>30 hrs</td>
<td>30</td>
<td>120</td>
</tr>
<tr>
<td>120 hrs</td>
<td>120</td>
<td>30</td>
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Efficient algorithms for Large Scale CO₂ inversion

P. K. Kitanidis
Dynamic monitoring – Spec KF

• Spectral Kalman Filter \(\rightarrow\) A Kalman Filter with better convergence than EnsKF, combining:
  • Low-rank representation of covariance matrices (hierarchical)
  • Matrix-free calculation for non-linear problems (i.e., no explicit calculation of Jacobian)
  • Avoid constructing and updating the full covariance matrix
  • Works best for high-frequency data
  • Can handle less smooth functions.
Dynamic monitoring – Spec KF

- Negligible difference from (full) Kalman Filter in estimation
- Computation time of Spec KF increases slowly with problem size
Synthetic Cases

The mathematical methods we have developed allow us to handle realistic synthetic cases, with high heterogeneity and diverse and numerous observations.
Applications

-\log (\text{permeability})

High k sandstone

Medium k sandstone

Low k sandstone

Shale

640 m x 640 m x 20 m synthetic domain

\sim 24,000 unknown permeabilities
Application to real sites

• Many challenges:
  • Diverse and sparse datasets
  • Poor prior knowledge
  • Even larger number of unknowns
  • Forward model simulation challenges
  • Tendency to oversimplify and undersimulate

• Fast algorithms cannot make up for the lack of information in the data; but they are necessary if we want to improve our rough prior models and operation design, as new data become available in real time.
Frio – 1 site

- Fresh-water (USDW) zone protected by surface casing
- Injection zones:
  - First experiment in 2004: Frio “C”
  - Second experiment in 2006: Frio “Blue”
- Oil production

Efficient algorithms for Large Scale CO₂ inversion

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Frio-I site

Two-well setup: injection and pumping well

Datasets

<table>
<thead>
<tr>
<th>Prior to CO2 injection</th>
<th>During CO2 injection</th>
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<tbody>
<tr>
<td>Pumping tests</td>
<td>CO2 saturation vertical profiles</td>
</tr>
<tr>
<td>Thermal tracer tests</td>
<td>Temperature vertical profiles</td>
</tr>
<tr>
<td>Conservative tracer tests</td>
<td>Pressure</td>
</tr>
</tbody>
</table>

- Quantitative geophysical data indicate two major preferential pathways that CO$_2$ followed upon injection.
  - One objective: confirm preferential flow pathways and refine prior geological model.
In Salah site

- Fewer data yet even larger scale:
  - 27 km x 43 km, 3 horizontal wells
- Even more complex physical problem
  - Fractured storage system
- Challenging the limits of forward and inverse modeling
In Salah site

- Challenge: To use high resolution InSAR data for surface deformation to calibrate geomechanical model and identify heterogeneity.
Summary

• Faster data-assimilation algorithms make it possible to answer crucial questions about CCS design and operation.

• We have developed inversion algorithms that provide big computational speed-up and storage cost savings:
  • Computational efficiency and accuracy validated using synthetic examples.
  • Currently being tested on real-sized domains with synthetic and real data.

• Project products will include guidance documents and user-friendly inversion packages that can be used to optimize CO$_2$ injection design and operation at real sites.
Approach

- Develop inversion methods that utilize fast linear algebra tools
  - Take advantage of structure and properties of the problem
  - Compute only what is needed
  - Compute at as high accuracy as needed
- Utilize modern computational environments (parallel computing)
- Can be used as black-boxes without specialized knowledge

- By doing that, we can:
  - Process large datasets in real time with modest computer resources
  - Provide estimates and their uncertainties to inform decision making
Appendix

• These slides will not be discussed during the presentation, **but are mandatory**
Organizational Chart

PI: Peter Kitanidis

Task 1: Project Management and Planning
Task Lead: Peter Kitanidis
Participants: Eric Darve, Judith Li, Hojat Ghorbanidehno, Amalia Kokkinaki

Task 2: Stochastic Inversion Development
Task Lead: Peter Kitanidis
Participants: Eric Darve, Judith Li, Hojat Ghorbanidehno, Amalia Kokkinaki

Task 3: Efficient Algorithms and GPUs
Task Lead: Eric Darve
Participant: Hojat Ghorbanidehno, Ruoxi Wang

Tasks 4 & 5: Methodology Testing/Application
Task Lead: Quanlin Zhou & Peter Kitanidis
Participants: Xiaoyi Liu, Judith Li, Amalia Kokkinaki, Jens Birkholzer

1Stanford University, 2Lawrence Berkeley National Laboratory
Project Team

At Stanford University:

• Sivaram Ambikasaran, PhD candidate in Computational and Mathematical Engineering (graduated in Aug 2013)
• Judith Li, PhD candidate in Civil and Environmental Engineering (CEE)
• Hojat Ghorbanidehno, PhD candidate in Mechanical Engineering (ME)
• Ruoxi Wang, PhD candidate in Computational and Mathematical Engineering (CME)
• Amalia Kokkinaki, post-doc in CEE
Project Team

At Lawrence Berkeley National Laboratory:

• Jens Birkholzer, collaborates on mathematical modeling issues
• Keni Zhang, collaborates on high-performance computing and the use of TOUGH2 model
• Xiaoyi Liu, collaborates on both forward modeling and inversion (left in May 2014)
# Gantt Chart

<table>
<thead>
<tr>
<th>Task</th>
<th>2013</th>
<th>2014</th>
<th>2015</th>
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</thead>
<tbody>
<tr>
<td><strong>DOE FY Quarter</strong></td>
<td>Q1</td>
<td>Q2</td>
<td>Q3</td>
</tr>
<tr>
<td><strong>Task 1.0. Project Management/Planning</strong></td>
<td></td>
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<tr>
<td>Subtask 1.1: Project Management Plan</td>
<td>A</td>
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<tr>
<td>Subtask 1.2: Project Planning and Reporting</td>
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<td>B</td>
<td></td>
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<tr>
<td><strong>Task 2.0. Development of Stochastic Inversion Methods</strong></td>
<td></td>
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<td>D1</td>
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<tr>
<td>Subtask 2.1: Development of Fast Bayesian Inverse Methods</td>
<td></td>
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<td>C1</td>
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<tr>
<td>Subtask 2.2: Development of Efficient Joint Inversion Methods for Dynamic Monitoring</td>
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<tr>
<td>Subtask 2.3: Fusion of Results from Separate Inversion of Multiple Different Data Sets</td>
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<tr>
<td><strong>Task 3.0. Development of Efficient Inversion Algorithms</strong></td>
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<td>D2</td>
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<tr>
<td>Subtask 3.1: Algorithms for Solving Large Dense Linear Systems</td>
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<td>C2</td>
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<tr>
<td>Subtask 3.2: High-Performance Implementation using GPUs</td>
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<tr>
<td><strong>Task 4.0. Testing of the Joint Inversion Methodology for a Synthetic Geologic Carbon Storage Example</strong></td>
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<td>E2</td>
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<td>Subtask 4.1: Generation of the “True” Fields of Porosity and Permeability of the Heterogeneous Storage Formation</td>
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<tr>
<td>Subtask 4.2: Generation of the Simulated Data of Hydro-Tracer-Thermal Tests and CO2 Injection Test</td>
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<tr>
<td>Subtask 4.3: Joint Inversion of the Simulated Data</td>
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<tr>
<td><strong>Task 5.0. Application of the Methodology to Test Sites</strong></td>
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<td>F3, F4</td>
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<tr>
<td>Subtask 5.1 Application to Test Site One</td>
<td></td>
<td></td>
<td>F1</td>
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<tr>
<td>Subtask 5.2 Application to Test Site Two</td>
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Project Workplan/SOPO Project Tasks

• Task 1: Project Management and Planning
  • Subtask 1.1: Project Management Plan
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    • Subtask 4.2.1: Creation of the Simulated Data for Hydro-Tracer-Thermal Tests Prior to CO₂ Injection
    • Subtask 4.2.2: Creation of the Simulated Data for CO₂ Injection Test
  • Subtask 4.3: Joint Inversion of the Simulated Data

• Task 5.0: Application of the Methodology to Test Sites
  • Subtask 5.1 – Application to Test Site One
  • Subtask 5.2 – Application to Test Site Two
Project Deliverables

1. Task 1.0 – Project Management Plan
2. Task 2.0 – Developed inversion algorithms and their demonstration cases, with the final joint inversion tool system, as documented in a quick-look report.
3. Task 3.0 – Developed fast large linear system solvers with different computational algorithms as documented in a quick-look report.
4. Task 4.0 – Test results of the joint inversion methodology for a synthetic Geologic Carbon Storage example as documented in a quick-look report.
5. Task 5.0 – Test results of application of the methodology to field test sites as documented in a quick-look report.
6. Task 5.0 – Validation of developed computational tools performance and cost as documented in quick-look report.
7. Project Data – Data generated as a result of this project shall be submitted to NETL for inclusion in the NETL Energy Data eXchange (EDX), [https://edx.netl.doe.gov/](https://edx.netl.doe.gov/).
Peer-reviewed publications


