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Overview

With recent advances in sensor and computation technology, unprecedented large volumes of hydro-geophysical and geochemical data sets can be obtained and processed to achieve high-resolution images of subsurface properties for more accurate and reliable subsurface flow and reactive transport prediction. For such problems, the $\mathbf{Principal}$ Component Geostatistical Approach (PCGA) [1,2,3] has been proposed

- **Jacobian-free** : no need to compute/store full Jacobian
- Forward model runs independent of the problem size : often runs much smaller number of simulations in practice
- Linear scalability : Matrix computation and storage costs grow linearly with respect the problem size
- Easy to implement : linked with any "black-box" multi-physics simulation models without invasive changes

Principal Component Geostatistical Approach

With **m** unknowns, $\mathbf{n_{obs}}$ measurements, and forward model(s) **h**, one needs:

- Jacobian matrix **H**, *i.e.*, sensitivity of the data to unknown parameters $\frac{\partial \mathbf{h}}{\partial \mathbf{s}}$
- Jacobian products with the prior covariance matrix \mathbf{Q} , *i.e.*, $\mathbf{H}\mathbf{Q}$ and $\mathbf{H}\mathbf{Q}\mathbf{H}^{\mathsf{T}}$

For large-scale/joint inversions (large m and n_{obs}), one faces several challenges such as

- time-consuming, invasive changes in multi-physics simulation code for efficient adjoint-state method implementation to evaluate Jacobian \mathbf{H}
- expensive Jacobian construction requiring $\mathbf{n_{obs}} \ (\geq \mathcal{O}(10^4))$ simulations
- prohibitive large dense matrix multiplication/storage for large $\mathbf{m} (\geq \mathcal{O}(10^6))$

In order to tackle these challenges, we developed PCGA that avoids expensive Jacobian evaluation and its matrix products (cross-covariance) by using a fast truncated **decomposition** [2,3] of the prior covariance

$$\mathbf{Q} \approx \mathbf{Q}_{\kappa} = \sum_{i=1}^{\kappa} \zeta_i \zeta_i^{\mathsf{T}}$$

and finite-difference approximation:

$$\mathbf{H}\zeta_i \approx \frac{1}{\delta} \left[h \left(\mathbf{s} + \delta \zeta_i \right) - h(\mathbf{s}) \right], \quad \mathbf{H}\mathbf{Q} \approx \Sigma_{i=1}^{\kappa} \left(H \zeta_i \right) \zeta_i^{\mathsf{T}}$$

Thus, PCGA can achieve a significant speed-up with reasonable accuracy, using simulation outputs without modifying multi-physics simulation code.

Python Software - pyPCGA

- pyPCGA: Python package for Principal Component Geostatistical Approach
- Supports $\mathcal{O}(N)$ fast linear algebra and (randomized) eigen-decomposition
- https://github.com/jonghyunharrylee/pyPCGA

Fast large-scale joint inversion for deep aquifer characterization using pressure and heat tracer measurements

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Synthetic Example : Frio site

scales linearly $(\text{Cost } \mathcal{O}(m\kappa^2))$

total $\kappa + 1$ simulations!





Figure: Synthetic true field generated by TProgS; pumping (red) and monitoring (blue) wells

TOUGH2-MP with module EOS1 was used for four dipole pumping tests between the center injection well and the other four wells. The monitoring network consists of a total of 8 multilevel monitoring wells with 10 monitoring ports. Transient pressure and zero-th moment of temperature ("total heat") data was used for the inversion performed on a Linux workstation with Intel 16 core 3.4 GHz processors and 100 GB RAM.

Results with pressure data inversion



Figure: the best estimate (left) and its estimation uncertainty (right) for pressure data inversion

Results with joint pressure and heat data inversion



Figure: the best estimate (left) and its estimation uncertainty (right) for joint data inversion



Figure: Data fitting for joint inversion; (a) observed vs. simulated pressure and (b) observed vs. simulated zero-th moment of temperature breakthrough curves.



- addition of heat tracer test data.

[1] Lee, Kokkinaki, Kitanidis, Fast Large-Scale Joint Inversion for Deep Aquifer Characterization Using Pressure and Heat Tracer Measurements, TPM, 2017,









	Results
(unknowns)	29800
	1 (injection), 4 (extraction), 8 (monitoring)
irements	4,000 (P only), 4,040 (P + 0-th moment of T)
or (std)	0.5 [m], 2.0 [°C]
TOUGH2 runs	1,353 (P only), 1,780 (P + T)
ours)	2.3 (P only), 8.0 (P + T)

pyPCGA + pyTOUGH

• Coming soon! a Python library for automating TOUGH2 simulations and parameter estimation for subsurface fluid and heat flow modeling: pyPCGA linked with pyTOUGH as a seemless computing environment.

Conclusion

• PCGA scales well with the number of observations to high-dimensional inverse problems with controlled accuracy (~ total $\mathcal{O}(100)$ per pumping test).

• Small-scale variability and low permeability inclusions are better identified with the

• Computational efficiency of pyPCGA enables assessing the information content of complex monitoring datasets for large scale subsurface characterization.

References

[2] Lee, Yoon, Kitanidis, Werth, Valocchi, MRI inverion, WRR, 2016

[3] Lee and Kitanidis, Large-Scale HT and Joint Inversion using PCGA, WRR, 201 [4] https://github.com/jonghyunharrylee/pyPCGA

Acknowledgment



For more info:

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