Abstract

Characterization of geologic heterogeneity at a geological carbon storage (GCS) system is crucial for cost-effective carbon injection planning and reliable carbon storage. With recent advances in computational power and sensor technology, large-scale fine-resolution simulations of multiphase flow and reactive transport processes have been available. However, traditional large-scale inversion approaches have limited utility for sites with complex subsurface structures such as faults and microfractures within the host rock matrix. In this work, we present a Bayesian inversion method with deep generative priors tailored for the computationally efficient and accurate characterization of GCS sites. Self-attention generative adversarial network (SAGAN) is used to learn the approximate subsurface property (e.g., permeability and porosity) distribution from discrete fracture network models as a prior and accelerated stochastic inversion is performed on the low-dimensional latent space in a Bayesian framework. Numerical examples with a synthetic fracture field with pressure and heat tracer data sets are presented to test the accuracy, speed, and uncertainty quantification capability of our proposed joint data inversion method.

1. Introduction

For the subsurface inverse problem (Carrera et al., 2005; McLaughlin & Townley, 1996; Oliver et al., 2008), spatially distributed geologic parameters such as permeability and porosity are estimated from noisy and sparse hydrogeophysical and geomechanical measurements such as pressure, temperature, displacement, seismic responses, and so on. Due to ill-posedness in the inverse problem, probabilistic frameworks have been implemented in order to account for the uncertainty that provides both unknown subsurface parameters and their corresponding uncertainty in a Bayesian statistical framework (e.g., Kitanidis, 1995; 2010; Lee et al., 2016). Typically pressure measurements from injection-extraction well operations are used for the site characterization, but unless many injection/extraction/observation wells are available, the subsurface characterization with sparse pressure measurements leads to poor predictions of other relevant quantities such as reactive transport. To overcome this issue, different sensing data can be used for joint inversion of pressure, saturation, temperature, and seismicity to identify the subsurface geologic connectivity during the CO₂ sequestration operations (Chen et al., 2018).

Still, one of the challenges in subsurface characterization is to identify highly heterogeneous permeability fields such as reservoirs with fracture networks. For such cases, traditional techniques using the Gaussian prior lead to smoothed, low-resolution images of subsurface properties with high estimation uncertainty due to the diffusive nature of the governing equations. Machine learning techniques such as deep generative models (Kang et al., 2022; 2021; Yoon et al., 2022; Kadeethum et al., 2021) have been actively studied to enforce the subsurface solution space on the relevant prior distribution constructed through multipoint geostatistics-based training images.

In this work, we present an application of an inverse modeling method based on the self-attention generative adversarial network (SAGAN) (Zhang et al., 2019) for characterizing a subsurface reservoir field at a reduced computational cost with improved accuracy compared to traditional inversion. The multiphysics model MOOSE-FALCON (Podgorney et al., 2021) is combined with our proposed Bayesian latent space inversion method. A synthetic application with single-phase flow pressure and heat tracer data is considered in this work for a two-dimensional, strongly heterogeneous permeability field estimation. Inversion of synthetic injecting tests is performed to show the usefulness and practicality of the proposed approach for geological carbon storage (GCS) sites characterization with reasonable accuracy before the
proposed method is extended and applied to 3D GCS applications.

2. Method

2.1. Deep Generative Modeling

Deep generative models (Goodfellow et al., 2014) have been studied because of their capability to approximate data distributions from training samples and generate new samples from the approximated data distribution in an efficient fashion. We use the self-attention generative adversarial network (SAGAN), which applies self-attention mechanism and spectral normalization (Zhang et al., 2019). SAGAN creates samples with detailed features from low-dimensional latent variables, which provides a solution for learning the distribution of subsurface properties such as fracture networks. 50,000 images with randomly generated fractures were used for training. There are 30 fractures at 0°, 30 fractures at 90°, and 40 fractures at 125° in each image, and the length of the fractures ranges from 5 to 20 pixels, similar to the images shown in Figure 3. The inversion solutions are constrained to the learned latent space while consistent with the observations. This will lead to our deep generative model-based parameterization of the permeability field:

\[ s = G(z) \]

where \( s \) is the permeability field and \( z \) is a \( k (\ll m) \)-dimensional (\( m \) represents the dimension of the permeability field) latent variable constructed from SAGAN. Using our generator \( G(z) \), the variable \( z \) in the context of the inversion problem represents the low-dimensional representation of \( s \).

2.2. Bayesian Inversion using Deep Generative Modeling

We use a Hierarchical Bayesian approach combined with SAGAN in this work for the inverse problem solver. The forward problem with the input of permeability field \( s \) can be defined in the form of the relationship

\[ y = h(s) + \varepsilon \]

where \( y \) is the observation (e.g., pressure, saturation, temperature, and displacement), \( \varepsilon \) is the observation and model uncertainty noise such as a Gaussian distribution with mean zero \( \varepsilon \sim \mathcal{N}(0, \mathbf{R}) \). Here, \( \mathbf{R} \) is the model/observation error matrix and \( h \) is the forward map. The inverse problem equivalent of Eq. 2 can be defined as a problem with unknown \( m \)-dimensional variable \( s \) (permeability) and \( n \) (noisy) observation \( y \) (pressure, temperature, and displacement). The Bayes’ rule allows us to evaluate a posterior distribution of \( s \) via

\[ p(s|y) \propto p(y|s)p'(s) = \int \theta p(y|s)p'(s|\theta)p'(\theta)d\theta \]

where \( p' (\cdot) \) represents the prior probability and \( \theta \) is a set of hyperparameters that models \( s \) in a hierarchical Bayesian framework.

In particular, with the generator \( G \), we can constrain variable \( z \) to follow a Gaussian distribution to ensure the regularity of the latent space:

\[ z \sim \mathcal{N}(0, \mathbf{\Sigma}) \]

We also assume that \( G \) is a deterministic map from \( z \) to \( s \) and the hyperparameter \( p'(\theta) \) such as neural network model parameters follows a delta distribution:

\[ \theta = \delta(\theta - \hat{\theta}) \]

This allows us to rewrite Eq. 3 in the form

\[ p(z|y) \propto p(y|z)p'(z) \]

\[ \propto \exp \left( -\left( y - h(G(z)) \right)^\top \mathbf{R}^{-1} \left( y - h(G(z)) \right) \right) \]

\[ \cdot \exp \left( -z^\top \mathbf{\Sigma}^{-1} z \right) \]

We explore this posterior equation to identify the latent variables consistent with observations through sampling or Bayesian approaches. Here we use a Bayesian approach to find the maximum a posteriori (MAP) estimate, which is the mode of the posterior distribution.

This task will require the computation of Jacobian \( J_l \) and at the \( l \)th iteration the computation is given by

\[ J_l = \frac{\partial h(G(z))}{\partial z} \bigg|_{z = z_l} = \frac{\partial h}{\partial s} \bigg|_{s = G(z')} \frac{\partial s}{\partial z} \bigg|_{z = z_l} \]

Note that \( \frac{\partial s}{\partial z} \) can be evaluated analytically using automatic differentiation (AD). This information can be provided at no additional computational cost in common libraries such as TensorFlow and PyTorch. Since the dimension of \( z \) is assumed to be significantly smaller than the dimension of \( s \), e.g., \( \text{dim}(z) \leq 100 \), we can also use a finite difference formulation to calculate the Jacobian matrix as an alternative to AD.

The workflow of coupling SAGAN and Bayesian inversion is shown in Figure 1. Using the trained generator, the 128 × 128 permeability field is generated with 16 latent variables. FALCON is then used as a forward model \( h \) in Eq. 2 and latent variables are updated using Bayesian inversion to maximize the negative logarithm of Eq. 6.

3. Synthetic Example Setup

The domain for heterogeneity characterization is a synthetic two-dimensional depth-integrated deep formation. As
shown in Figure 2, a 640 m × 640 m domain was discretized into 128 × 128 meshes. This image shows fractures with 3 orientations: 0°, 90°, and 135°, and this image was not used for training. A constant pressure of 34 MPa and 30 MPa was imposed on the western and eastern boundaries, respectively. A constant temperature of 473.15 K and 423.15 K was applied to the western and eastern boundaries, respectively. One injection well was placed at [190 m, 180 m] for transient simulations and nine monitoring wells were used for observation. To simplify the problem formulation, we inject heat tracer (lower temperature water than one in the deep formation) into the aquifer, and pressure and temperature data were measured every 100 s at the monitoring wells. The injection rates linearly increased from 0 to 5 g/s from 0 s to 1000 s. The injection temperature was a constant value of 323.15 K. The values of the material parameters are shown in Table 1. Permeability and porosity are heterogeneous as shown in Figure 3, using the same image but assigning different values. For permeability, the fractures (white lines) were assigned $10^{-14} \text{m}^2$, and other areas were assigned $10^{-16} \text{m}^2$. For porosity, the fractures were assigned $10^{-3}$, and other areas were assigned $10^{-4}$.

Figure 2. Model settings. 34 MPa pressure and 473.15 K temperature were applied to the western boundary. 30 MPa pressure and 423.15 K temperature were applied to the eastern boundary. The red circles represent monitoring wells, and the red cross shows the injection well location.

4. Preliminary Results

Figure 4 shows the estimation of the permeability field which shows reasonable characterization of subsurface fracture features because of the informative training data for the deep generative model construction. Figure 5 shows the fitting results of pressure and temperature data. Gaussian noise with standard deviations of 1% of the mean was added to the observed pressure and temperature data, respectively. The fitting errors are also shown as the root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{N_k} \sum_{i=1}^{N_k} (k_{i}^{\text{est}} - k_{i}^{\text{true}})^2} \quad (8)$$

where $k_{i}^{\text{est}}$ indicates the estimated parameter value and $k_{i}^{\text{true}}$ is the true value, $N_k$ is the total number of parameters.

The RMSE of pressure data fitting is 0.351 while the RMSE of temperature data fitting is 4.266, about the same level as the error added. We estimated permeability and porosity together and the accuracy of the porosity estimate is similar to the permeability estimation.

5. Conclusion

We implemented a deep generative model-based inversion approach to perform joint data inversions and presented reasonable inversion results with affordable forward model runs. The proposed method transforms an inverse problem with the computational cost associated with the number of observations into an approximately same problem with a constant number (≈total O(100)) of simulations so that one would expect a great computational gain in solving high-dimensional inverse problems. In the examples presented,
the estimated fields captured important permeability features, i.e., fractures, due to the informative prior used in the training. It is also observed that the estimate with improved accuracy was obtained at a much smaller computational cost than traditional methods, allowing for the characterization of a 2D deep reservoir in less than 10 minutes on a workstation equipped with 48 CPU cores. Joint data inversion from pressure and heat tracer with the pre-trained deep generative model can be beneficial to identify connectivity features in the site without considerably increasing the computational costs.

6. Broader Impact

Understanding the distribution of subsurface properties such as permeability and porosity is important for CO$_2$ storage management. Our work aims to develop an efficient and fast inverse modeling framework to estimate key parameters of subsurface storage sites, then better predict flow and transport processes. Well placement and CO$_2$ injection planning will benefit from characterization of subsurface properties and predictions.

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References


