Ensemble-based seismic history matching with data reparameterization using convolutional autoencoder

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Summary

In this work, we propose an ensemble-based seismic history matching approach to predict reservoir properties, i.e. porosity and permeability, with uncertainty quantification, using both production and time lapse seismic data. To avoid the common underestimation of uncertainty in ensemble-based optimization approaches, and to make the computation feasible, we introduce the convolutional autoencoder to re-parameterize seismic data into a lower dimensional space. We then apply the Ensemble Smoother with Multiple Data Assimilation to optimize an ensemble of reservoir models using the production and re-parameterized seismic data. The proposed methodology is tested on a 2D synthetic case. The inversion results indicate that the method can largely improve the characterization of reservoir models compared to the history-matching scenario with production data only.

Introduction

History matching is an inverse problem that plays a key role in reservoir engineering to estimate reservoir properties, such as porosity and permeability from production data and potentially geophysical measurements (Oliver et al., 2008). In the last decades, many algorithms have been developed for history matching. At the early stage, efforts were mainly dedicated to gradient-based deterministic approaches, such as gradient descent, Gauss-Newton and Levenberg-Marquardt algorithms, in which a single deterministic solution can be obtained by minimizing or maximizing a pre-defined objective function based on the gradient and/or Hessian matrix. However, the fluid flow simulation that links reservoir properties to production data requires the solution of a set of large-scale partial differential equations (PDEs). As a result, it is time-consuming to evaluate and memory-demanding to storage the Jacobian and Hessian matrix of measurements with respect to the model parameters. Although the adjoint approach can mitigate these issues (Chen et al. 1974), its implementation is usually challenging and not available in commercial reservoir simulators. Furthermore, deterministic approaches can only provide a single reservoir realization and are intrinsically not able to evaluate the associated model uncertainty.

To avoid the aforementioned limitations, ensemble-based methods, i.e. ensemble Kalman filter (EnKF) (Evensen, 1994) and ensemble smoother (ES) (van Leeuwen and Evensen, 1996) as well as their iterative forms, are becoming popular in history matching in recent years. In contrast to deterministic gradient-based methods, ensemble-based methods approximately estimate the sensitivity matrix from an ensemble of models. Such methods are generally derivative-free and independent from the reservoir simulators. Moreover, ensemble-based methods can generate multiple reservoir realizations that honor the geophysical measurements and production data, from which the associated model uncertainty can be quantified.

In traditional history matching studies, only production data, such as bottom hole pressures (BHPs), oil production rates (OPRs) and water cuts (WCTs), are assimilated to update the initial reservoir models. However, the production data from wells are sparse, and cannot capture the spatial features of reservoirs. Thanks to the dense coverage of the reservoir, time-lapse seismic can complement the information provided by production data, and can be used to improve the reservoir characterization. Therefore, seismic history matching has gained increasing attention. However, the assimilation of seismic datasets is challenging, due to the extremely large size of seismic data. As a consequence, additional limitations arise, such as intensive computation, and the phenomenon of ensemble collapse in which the model uncertainty is severely underestimated (Liu and Grana, 2018). Local analysis and data re-parameterization are two common and effective methods to handle these problems.

In this work, we apply the Ensemble Smoother with Multiple Data Assimilation (ES-MDA) (Emerick and Reynolds, 2013) to optimize reservoir models using both production and time lapse seismic data. Unlike the sequential data assimilation method, ES computes a global update by simultaneously assimilating all available data and avoids restarting the simulation from the initial time step, every time new data are assimilated. ES-MDA is an iterative version of ES, which is suitable to handle nonlinear cases. In ES-MDA, the ensemble is updated iteratively by assimilating the data multiple times with an inflated covariance to achieve better data match. Due to the size of seismic data, such approach would require a large number of ensemble models. In our inversion approach, we introduce a deep learning method, the convolutional autoencoder (Masci et al., 2011), for the re-parametrization of seismic data to avoid the phenomenon of ensemble collapse due the high dimensionality of data. The convolutional autoencoder is an unsupervised method that aims to learn a sparse representation for a set of data. Thanks to convolutional layers in the network, it is able to exploit and capture spatial patterns in the data space, and thus outperforms other dimensionality reduction approaches, such as principle component analysis (PCA), optimization-PCA (OPCA) and discrete cosine transform (DCT) (Laloy et

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al, 2017). As a proof-of-concept, a 2D synthetic case of channelized reservoirs is adopted to verify the feasibility and analysis the performance of the proposed method.

Theory

Seismic history matching aims to estimate a set of models of reservoir properties, including porosity and permeability, given the production and seismic data. In general, we can describe the problem as the following mathematical form:

$$\mathbf{d} = \boldsymbol{f}(\mathbf{m}) + \mathbf{e} \tag{1}$$

where $\mathbf{d}$ represents the observations; $\mathbf{m}$ represents the unknown reservoir properties; $\boldsymbol{f}$ represents the assumed physical model that maps $\mathbf{m}$ into $\mathbf{d}$; and $\mathbf{e}$ is the associated error term in the measurements.

More specifically, the physical model in history matching is governed by a set of PDEs that describes the multi-phase flow in porous media. Because those PDEs generally involve high dimensional model variables and are highly nonlinear, it is extremely time-consuming to evaluate the Jacobi and Hessian matrix in gradient-based optimization methods. Instead, ensemble-based methods approximate the sensitivity matrices using an ensemble. For this reason, in this work, we adopt ES-MDA as the optimization method. It updates the ensemble of prior models by assimilating all data simultaneously multiple times with an inflated measurement error covariance matrix. Each data-assimilation step can be interpreted as a Bayesian updating step in which the conditional distribution of the model parameters is approximated by estimating the conditional mean and covariance matrix from the ensemble of models. From a mathematical point of view, the updating equation of model parameters $\mathbf{m}$ in a single iteration can be written as

$$\mathbf{m}_j^u = \mathbf{m}_j^p + \widetilde{\mathbf{K}}\big(\tilde{\mathbf{d}}_j - \mathbf{d}_j^p\big) \tag{2}$$

for $j = 1, \ldots, N_e$, with N_e denoting the number of ensemble members, subscripts u and p represent the updated (current iteration) and prior (previous iteration) variables respectively, and $\widetilde{\mathbf{K}}$ denotes the Kalman gain matrix estimated from the ensemble which can be expressed as

$$\widetilde{\mathbf{K}} = \mathbf{C}_{\mathbf{md}}^p\big(\mathbf{C}_{\mathbf{dd}}^p + \mathbf{C}_{\mathbf{d}}\big)^{-1} \tag{3}$$

where $\mathbf{C}_{\mathbf{md}}^p$ is the cross-covariance matrix between the prior vector of model parameters $\mathbf{m}^p$ and the vector of the corresponding predicted data $\mathbf{d}^p$; $\mathbf{C}_{\mathbf{dd}}^p$ is the $N_d \times N_d$ covariance matrix of the predicted data (N_d being the number of assimilated data); $\tilde{\mathbf{d}}$ represents a stochastic perturbation of the observed data sampled from a Gaussian distribution $\mathcal{N}(\mathbf{d}, \mathbf{C}_{\mathbf{d}})$ with $\mathbf{d}$ denoting the N_d-dimensional vector of observed data and $\mathbf{C}_{\mathbf{d}}$ denoting the $N_d \times N_d$ covariance matrix of observed data measurement errors.

In theory, ES is equivalent to a single Gauss–Newton iteration with a full step and an average sensitivity estimated from the prior ensemble; therefore, in nonlinear cases, it is desirable to perform it iteratively with covariance inflation to achieve a satisfactory match between predicted data and measurements. The implementation of the ES-MDA algorithm can be described as follows:

1. Define the number of iterations N and the inflation coefficients α_i for $i = 1, \ldots, N$ with the constraint $\sum_{i=1}^{N} \alpha_i^{-1} = 1$.
2. For $i = 1$ to N:
   (a) Run the forward models and compute the predictions $\{\mathbf{d}^p\}_{1,\ldots,N_e}$, where N_e is the number of ensemble members.
   (b) Perturb the observation of each ensemble member using $\tilde{\mathbf{d}} = \mathbf{d} + \sqrt{\alpha_i}\mathbf{C}_{\mathbf{d}}^{1/2}\mathbf{z}_{\mathbf{d}}$, where $\mathbf{z}_{\mathbf{d}} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_{N_d})$.
   (c) Update the ensemble using Equations 2 and 3 by replacing $\mathbf{C}_{\mathbf{d}}$ with $\alpha_i\mathbf{C}_{\mathbf{d}}$.

Although seismic data can provide valuable additional information for history matching, its high dimensionality also makes the evaluation and storage of the Kalman gain matrix challenging, and could lead to the typical phenomenon of ensemble collapse in ensemble-based methods. To solve the aforementioned problems, we introduce the convolutional autoencoder to re-parametrize seismic data into a low dimensional feature space.

The convolutional autoencoder is a widely-used and powerful deep learning model in computer vision and speech recognition. An autoencoder neural network is an unsupervised learning method for which the input is the same as the output. It works by compressing the input into a small number of hidden features in latent space (encoding), and then reconstructing the output from the sparse hidden features (decoding), which can be expressed as the following mathematic form

$$x = h^{-1}(h(x)) \tag{4}$$

where x is the input data, and h is the function the autoencoder tries to learn.

In fact, a simple autoencoder with linear activation functions is approximately equivalent to PCA. But an autoencoder that contains convolutional layers (LeCun et al., 1998) connected with nonlinear activation functions, has the ability to discover spatial correlations of data, and therefore can obtain

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a much more accurate sparse representation. The resulting neural network is called a convolutional autoencoder. In addition, we can add some noise to the input data in the training stage to make the neural network robust to noise.

The architecture of the convolutional autoencoder in this study is as illustrated in Figure 1. It is composed of two symmetrical parts: encoder for compression and decoder for reconstruction. Each rectangle in the figure represents a convolutional layer and a pooling layer, and each layer is connected with a nonlinear activation function (ReLU). From the architecture, we can conclude that 100×100 seismic can be sparsely represented by 2×7×7 latent-space features. To test the method, we generate a synthetic dataset consisting of 1000 synthetic reservoir models and their computed seismic response to train the neural network. Figure 2 shows the seismic data of two randomly selected prior models and their corresponding reconstructed data. The results show that the extracted hidden features can satisfactorily capture the spatial trend of the channel in the reservoir. In the proposed method, we apply this approach to seismic data re-parameterization in the ES-MDA seismic history matching process.

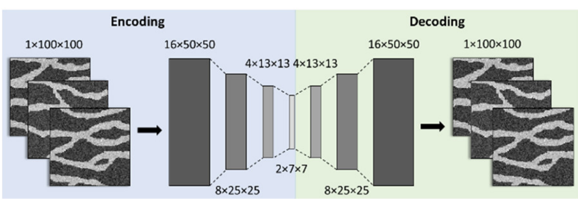

Figure 1: Architecture of the convolutional autoencoder: each gray rectangle represents a convolutional layer and a pooling layer, and both layer is connected with a nonlinear activation function (ReLU).

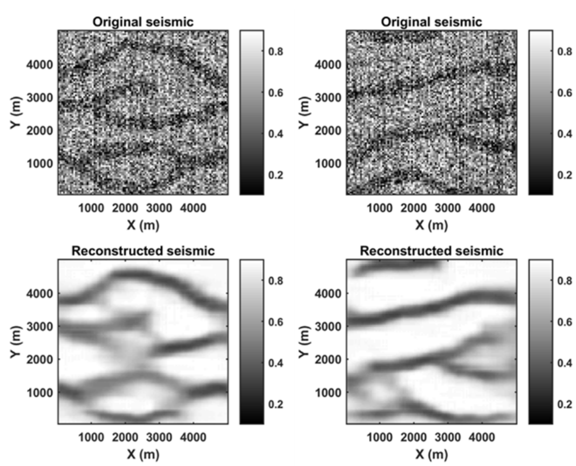

Figure 2: Test seismic data and the corresponding reconstructed seismic from the convolutional autoencoder in Figure 1: normalized original seismic (top); normalized reconstructed seismic (bottom).

Application

In this section, we apply the proposed method to a 2D synthetic case to verify the feasibility and analysis its performance. The synthetic model is a channelized reservoir with two fluid phases (water and oil), and geometrical model consists of 100 grid blocks in both x- and y-direction with the grid block size 50 m × 5 m. The locations of injection and production wells are shown in Figure 3(a). The model properties include permeability and porosity (Figure 3(a) and 3(b)). The corresponding production data, i.e. BHPs of injectors, and OPRs and WCTs of producers, are simulated by the Matlab Reservoir Simulation Toolbox (Lie, 2016) every 120 days for 10 years (Figure 3(c)-3(e)). In addition, we simulated the time lapse seismic data, including a base survey at the beginning of production and a monitor survey at the 5th year. The seismic response was generated by embedding the reservoir in two shale layers. Thus, the total number of observations is 20,450 (450 production measurements and 20,000 seismic observations). For the purpose of verification, the reference models of permeability and porosity are assumed to be unknown to us, and the goal of the proof-of-concept is to estimate them given the above production data and time lapse seismic.

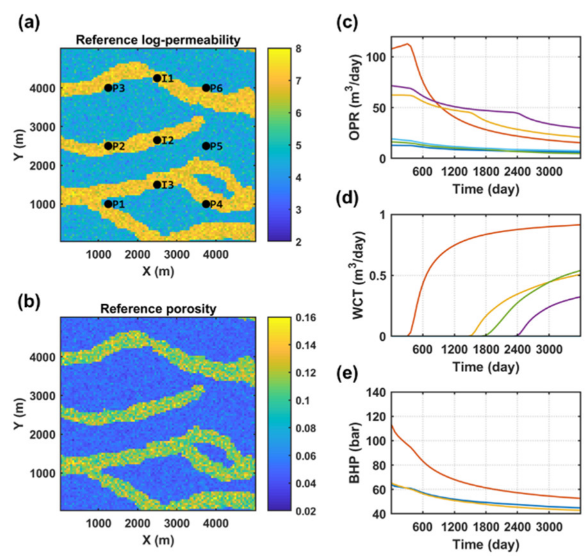

Figure 3: Reference models and production data: (a) reference log-permeability (black dots represent the location of injectors (I1, I2 and I3) and producers (P1, P2, P3, P4 P5 and P6)); (b) reference porosity; (c) oil production rates (OPRs) of producers; (d) water cuts (WCTs) of producers; (e) bottom hole pressures (BHPs) of injectors.

To evaluate the performance of our proposed method, we consider two history-matching scenarios: production data only (S1); and both production and re-parameterized seismic

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data (S2). In both scenarios, we first generate 500 prior reservoir realizations of permeability and porosity from the variational autoencoder (as Laloy et al., 2017), which constitute the initial ensemble. The average of the ensemble models is a model with spatially invariant porosity and permeability. Then perform the reservoir simulation for each prior ensemble member to obtain the production data. In the S2 case, we also generate the corresponding time lapse seismic, and apply the trained convolutional autoencoder to reparametrize the data into a lower dimensional feature space. Then, ES-MDA is performed to update the prior ensemble iteratively by assimilating the production data only in the S1 case and both production and re-parameterized seismic data in the S2 case. In both scenarios, the number of data assimilation is fixed and equal to 4.

Figures 4 and 5 show the final updated reservoir models of permeability and porosity for S1 and S2 respectively. Compared to the reference models, the posterior ensemble mean of the S2 case can accurately capture the spatial trend of the reservoir model, whereas in the S1 case, we can only capture the trend near the wells. Furthermore, the additional seismic information is helpful to reduce the model uncertainty.

Conclusions

In this work, we propose an ensemble-based history matching method with the convolutional autoencoder for data re-parameterization to estimate reservoir properties (permeability and porosity) using both production and time-lapse seismic data. We apply the approach to a 2D synthetic case to validate the method. The results show that the convolutional autoencoder can sparsely represent the seismic data by exploiting the spatial patterns, and the inversion results obtained by assimilating the re-parameterized seismic data into reservoir models largely improve the reservoir modeling process.

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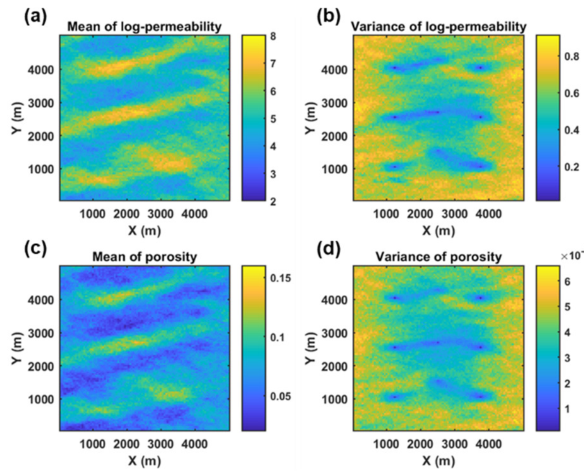

Figure 4: Inversion results of S1: (a) mean of log-permeability; (b) variance of log-permeability; (c) mean of porosity; (d) variance of porosity.

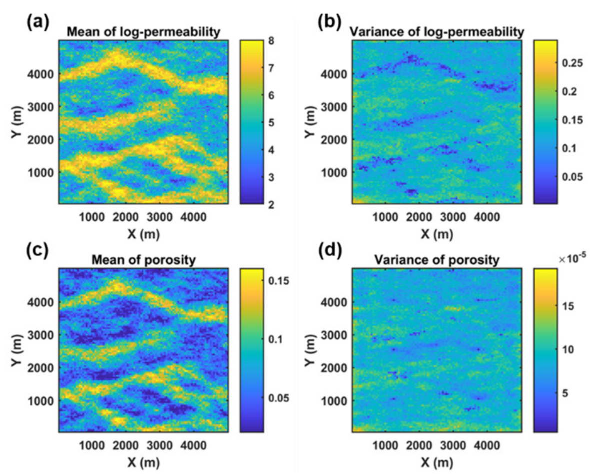

Figure 5: Inversion results of S2: (a) mean of log-permeability; (b) variance of log-permeability; (c) mean of porosity; (d) variance of porosity.

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