Joint seismic and electromagnetic inversion for reservoir mapping using a deep learning aided feature-oriented approach

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Summary

As more and more types of geophysical measurements informing about different characteristics of subsurface formations are available, effectively synergizing the information from these measurements becomes critical to enhance deep reservoir characterization, determine interwell fluid distribution and ultimately maximize oil recovery. In this study, we develop a feature-based model calibration workflow by combining the power of ensemble methods in data integration and deep learning techniques in feature segmentation. The performance of the developed workflow is demonstrated with a synthetic channelized reservoir model, in which crosswell seismic and electromagnetic (EM) data are jointly inverted.

Introduction

Joint inversion of multiple sources of geophysical data has demonstrated its great potential in enhancing the fidelity of inverted reservoir models. The main idea behind the joint inversion is to synergize the information contained in different types of geophysical datasets into an integrated inversion scheme for better recovery of reservoir properties and structures (Moorkamp, 2017). Seismic and electromagnetic (EM) data inherently exhibit complementary sensitivities to reservoir rock and fluid properties and are increasingly used for joint inversion. In general, seismic data provide effective information about the reservoir structure while EM data are sensitive to fluid content discriminating between oil and salt water. Crosswell seismic and EM techniques, in particular, reaching deep into the reservoir to produce a cross-sectional mapping of geophysical properties between wells, fill an intermediate resolution gap between well logs and surface measurements (Al-Ali et al., 2009). The recent field studies presented by Marsala et al. (2008, 2017) showed the ability of crosswell EM tomography to deliver useful interwell resistivity and saturation mapping even at widely-spaced wells.

There has seen a growing interest in enhancing reservoir characterization through history matching of different geophysical measurements (Katterbauer et al., 2016; Liang et al., 2016). Different from the integration of production data that are commonly used for history matching, the approach to integrate geophysical data is not unique. As discussed in (Zhang et al., 2020), there are three different approaches to extract information from the raw data to calibrate reservoir models. Each approach involves different degrees of forward modeling and inversion processes. Zhang et al. (2020) proposed an ensemble-based model calibration workflow in which the interpreted resistivity field from EM inversion are integrated through a feature-oriented approach. They found that the performance of the proposed workflow depends on the quality of inversion results and it is susceptible to the bias and propagated errors introduced by the inversion. To mitigate this adverse effect, Zhang and Hoteit (2020) extended the workflow by incorporating the joint seismic and EM inversion to reduce the interpretative ambiguities of inverted reservoir properties.

Feature segmentation plays an important role in the feature-oriented integration approach, whose performance relies on the quality of extracted information. In this respect, deep learning, utilizing a hierarchical level of artificial neural networks to carry out the process of machine learning, has shown very promising results in pattern recognition and extraction. Deep learning can learn high-level features from data so that the need of domain expertise and manual feature extraction is avoided. In this study, we exploit the potential of deep learning in feature segmentation to strengthen the feature-based model calibration workflow developed by Zhang and Hoteit (2020).

Method

We extend the feature-oriented ensemble model calibration workflow introduced in (Zhang and Hoteit, 2020) by facilitating the feature segmentation process with deep learning techniques. Figure 1 shows the developed workflow which consists of two main steps. The rock cross-properties (Dell'Aversana et al., 2011) including water saturation and porosity, which links with both seismic velocities and formation resistivity, are firstly estimated by joint seismic and EM inversion (i.e., orange loop). Subsequently, the remaining uncertain reservoir properties such as permeability are updated by being conditioned on the inverted saturation fields (i.e., blue loop). The core of the workflow is based on ensemble assimilation methods that provide a flexible framework, under which any uncertain model parameters can be estimated and various types of measurements can be readily incorporated. Ensemble assimilation methods approximate the Bayesian formulation of data integration using a Monte Carlo approach, in which the model uncertainties are represented by an ensemble that is a group of realizations of uncertain model variables. The ensemble itself provides an empirical estimate of the probability distribution of the model variables conditioned on the data. The developed workflow adopts the start-of-the-art ensemble methods (e.g., Chen and Oliver, 2013; Emerick and Reynolds, 2013) that showed robust performances in real field history-matching applications.

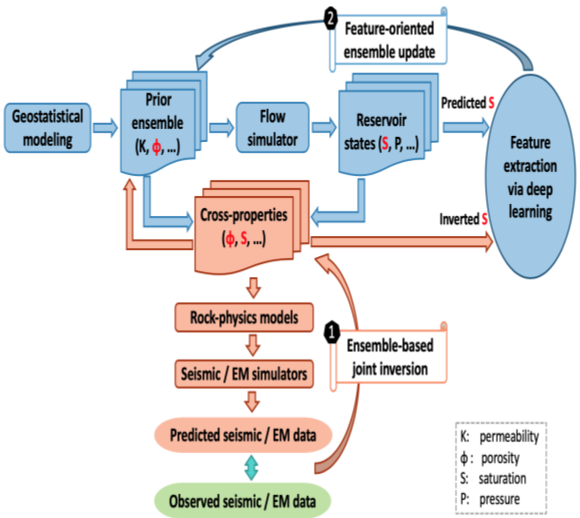

Figure 1: Workflow for reservoir property mapping from joint seismic and EM inversion via deep learning aided feature-based approach.

The workflow in Figure 1 starts with the generation of the initial ensemble of model parameters (porosity and permeability are considered here) through geostatistical modeling based on prior information. Proper sampling of the prior ensemble is essential to ensure the performance of ensemble methods, considering the fact that the posterior solution is constrained within the subspace of the prior ensemble of model parameters. Seismic and EM measurements are then integrated through the following two-step procedure. The extension to include other types of model parameters and measurements is straightforward.

Step 1: ensemble-based joint inversion

This step exploits the potential of joint inversion for enhanced mapping of rock cross-properties using ensemble assimilation methods. Based on the generated ensemble of porosity and permeability, the prior ensemble of saturation fields is sampled by running a reservoir flow simulator up to the seismic and EM survey time. To simulate the seismic and EM responses, the forward observation model consists of two components including rock physics modeling and seismic-EM simulators. Rock-physics models link the rock cross-properties, i.e., porosity and saturation, to seismic velocities and formation resistivity. With the inputs from the established rock-physics models, predicted seismic and EM data are then obtained from the corresponding forward simulators. For more detail about the forward observation model used in this study, the reader is referred to (Zhang and Hoteit, 2020). Conditioning on the observed seismic and EM measurements, the prior ensemble of porosity and saturation is updated.

Step 2: feature-oriented ensemble update

The objective of this step is to update the remaining uncertain model parameters based on the inverted porosity and saturation fields in Step 1. Instead of integrating the inverted saturation field directly, we employ a feature-based approach that conditions on the shape information of extracted features from the attribute of interest. This is primarily motivated by the fact that the information contained in the shape of a feature (if can be extracted coherently) usually carries the most essential and reliable information contained in the original data. Specifically, we extract front positions from the inverted saturation field using deep learning techniques.

Figure 2 outlines the process of feature segmentation using a deep learning approach, which consists of two stages. The process starts with the training stage, at which we use a pre-trained convolutional neural network (CNN) Alexnet model (Iandola et al., 2016), and fine-tune the network to find the training model with the target input dataset. At the second stage, the training model is used to extract the target feature from input image, in combination with a pre-processing step for image enhancement and noise reduction (Hittawe et al., 2017).

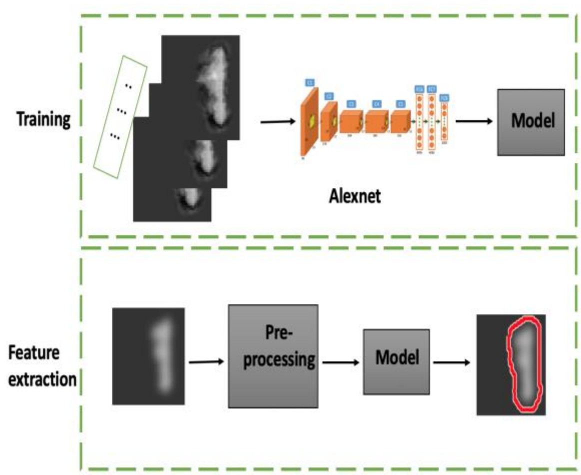

Figure 2: Process of feature segmentation using deep learning

The identified front positions are then integrated by a distance parameterization method proposed in Zhang and Leeuwenburgh (2017) to update the prior ensemble of permeability fields.

Workflow deployment case

To examine the performance of the developed model calibration workflow, we choose a reservoir model that was used in Zhang and Hoteit (2020), which is a 2D channelized reservoir model with a crosswell configuration for EM and seismic surveys.

Model description

Figure 2 shows the reference porosity and log-transformed permeability fields (used to generate observations) with channel-like high-permeable flow corridors. The model dimensions are 45 × 45 with a uniform grid size of 5 m in horizontal directions and 20 m in vertical direction. There are two facies types in which the channel facies (sand) is characterized by high permeability and porosity while the background facies (shale) is the opposite. The facies realizations are first generated by a multipoint-based geostatistical algorithm, based on which the realizations of porosity and log-permeability are generated by the sequential Gaussian simulation algorithm using an exponential variogram model with an isotropic range of 8 gridblocks. The reference model is randomly drawn from the generated realizations. The fluid system consists of two immiscible phases (oil and brine) with a connate water saturation of 0.2, residual oil saturation of 0.2, and initial formation pressure of 310 bar. As shown in Figure 2, there are two horizontal wells, one producer (shown as solid black circles) and one injector (shown as white crosses), with an interwell separation of 125 m. The producer is under bottom-hole pressure (BHP) control at 138 bar, and the injector is on rate control at 200 $\mathrm{sm}^3/\mathrm{day}$.

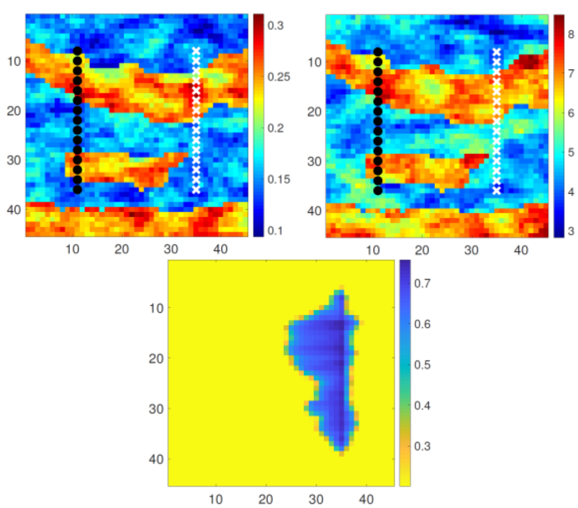

Figure 2: The reference porosity (top left) and log-permeability (top right) fields from which synthetic seismic and EM data are generated. The true saturation field for the crosswell seismic and EM surveys conducted at day 60 (bottom).

Measurement setup

For the crosswell setting of both seismic and EM surveys, transmitters and receivers are placed in the boreholes of the producer and the injector, respectively. There are 15 transmitters and 15 receivers that are uniformly distributed from the heel to the toe of each horizontal well. For the EM survey, the transmitters are axial magnetic dipoles, and the measured data are the horizontal components of the magnetic fields. The frequency of operation is 500 Hz. For the seismic survey, monopole sources are used, and the receivers measure scalar pressure fields. The frequencies of 20, 60 and 100 Hz are chosen for the inversion. The seismic and EM surveys are conducted at day 60. The true saturation field at the survey time is shown in Figure 2 (bottom). The synthetic seismic and EM data generated from the reference reservoir model are perturbed with 5% Gaussian random white noise.

Ensemble assimilation setup

The initial ensemble consists of 100 members. An iterative ensemble smoother developed by Chen and Oliver (2013) is used together with a bootstrap-based Kalman gain localization method introduced in Zhang and Oliver (2010) to reduce the effect of sampling errors and rank deficiency caused by the limited ensemble size.

Results from Step 1

Figure 3 shows the distribution of data mismatch during the joint integration of seismic and EM data. The data mismatch is calculated as follows

$$S_d(\boldsymbol{m}_j) = \left(\boldsymbol{d}_{obs} - \mathbf{g}(\boldsymbol{m}_j)\right)^{\mathrm{T}} \boldsymbol{C}_D^{-1} \left(\boldsymbol{d}_{obs} - \mathbf{g}(\boldsymbol{m}_j)\right), \quad (1)$$

where $\boldsymbol{d}_{obs}$ is a vector of observed data, $\mathbf{g}(\cdot)$ denotes the operator mapping the model parameters $\boldsymbol{m}$ to predicted data, $\boldsymbol{C}_D$ is observation error covariance, and the subscript j is the index of ensemble member. In a similar way, there is a consistent reduction in the root-mean-square error (RMSE) of the updated ensembles of porosity and water saturation as shown in Figure 3.

Figure 4 shows the updated ensemble means of porosity and water saturation fields. It is clear that both porosity and saturation mean fields reproduce the main features observed in the corresponding true models.

Results from Step 2

To extract saturation fronts from the inverted saturation fields, we proceed with the feature extraction using deep learning. In addition to the inverted saturation fields, the training dataset is also composed of the predicted saturation fields obtained from the flow simulation using the prior permeability ensemble. The size of training dataset is 200. Figure 5 shows the distribution of extracted fronts from the inverted and predicted saturation ensembles using the trained CNN model. We take the front positions (red dots) extracted from the inverted mean saturation field as the observations, which closely align with the ones (greed circles) extracted from the true saturation field. Uncorrelated distance measurement errors are assumed with a standard deviation of one grid cell length.

Figure 6 shows the final match of saturation fronts and the mean of the updated ensemble of permeability fields. The updated ensemble mean of permeability captures the upper high-permeable channel structure observed in the reference model, indicating the essential information carried by the interpreted saturation front.

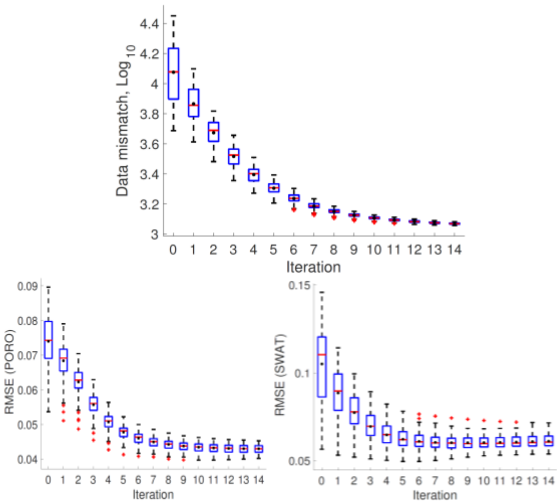

Figure 3 (top): Distribution of data mismatch along with iteration for joint integration of seismic and EM data. Distribution of RMSE of updated porosity (bottom left) and water saturation (bottom right) ensembles along with iteration.

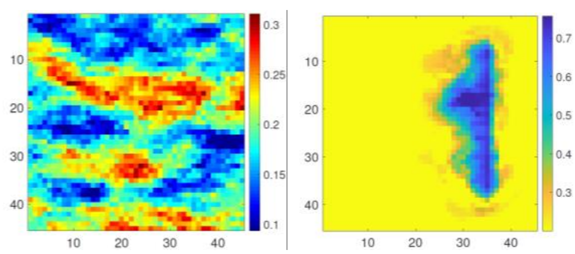

Figure 4: The updated ensemble means of porosity (left) and water saturation (right) fields.

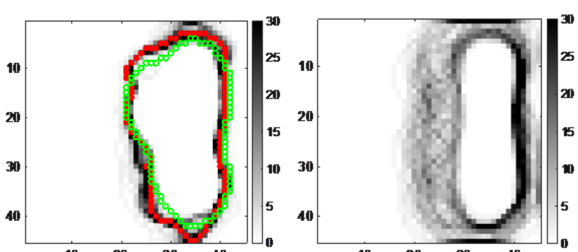

Figure 5: Extracted saturation fronts from the inverted saturation ensemble (left) and the predicted saturation ensemble (right) corresponding to the prior permeability ensemble. The red and green dots denote the fronts extracted from the inverted saturation mean and true saturation fields respectively. The grayscale indicates the count of occurrence of the water front at a location. The scale is truncated for better display.

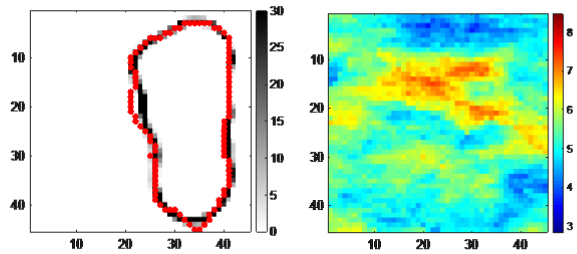

Figure 6: The final match of saturation fronts (left) and the mean (right) for the updated ensemble of permeability fields.

Conclusions

We developed an ensemble-based model calibration workflow focusing on the integration of seismic and EM measurements via a deep learning aided feature-oriented approach. The workflow divides the model calibration process into two steps. The first step involves a joint inversion of seismic and EM data, as a result of which the uncertain cross-properties, such as saturation and porosity, are updated. In the second step, the remaining model parameters are calibrated based on the updated cross-properties. The inverted saturation information is integrated using a distance parameterization method combined with a feature extraction deep learning approach. The experimental results suggest that the developed workflow provides a novel and effective way to incorporate the information from multiple sources of geophysical datasets into reservoir models. Ultimate goal is to maximize productivity by means of reducing the uncertainties on reservoir characterization and deep fluid distribution mapping in the interwell volumes of the reservoirs, where only indirect geophysical measurements are currently available.